Essays on Migration, Social Networks and Employment

by

Claire Le Barbenchon

Public Policy Studies and Sociology
Duke University

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Dissertation submitted in partial
fulfillment of the requirements for the degree
of Doctor of Philosophy in Public Policy Studies in the
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ABSTRACT

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Abstract

Immigrants rely on social networks upon arrival to their country of destination to access resources, find a job, and begin the process of incorporation. However, the contours of how and under what circumstances networks support a job search or facilitate assimilation remain unexplored. In this dissertation, I look at the intersection of migration, social networks and employment to shed light on both the limitations and benefits of social networks for immigrant incorporation.

In Chapter 1, I study whether return migrants use social networks to find a job when they return to their home country. In doing so, I contribute to the academic debate on whether immigrants lose or maintain their connections to friends and family when they leave. Using Colombia as a case study, I draw on data from two years of Colombian nationally representative household surveys conducted in 2016 and 2017. I use a Difference-in-Differences strategy and exploit a mass deportation event of Colombian migrants from Venezuela in 2015 which prompted a wave of return-migrants. This yields three main findings: (1) Return migrants are more likely to use networks in their search than never migrants; (2) social networks are a last resort in return migrants' job search, and (3) jobs found through networks for return migrants may be lower quality than jobs found through other means. This paper contributes to

the literature on return migrant integration, and speaks to an important question in the literature: Will friends and family still be there for you after you've left?

In Chapter 2, co-authored with Giovanna Merli and Ted Mouw, we study how immigrants' personal networks are related to their migration experience and key indicators of assimilation. We draw on novel data that includes network data for over 500 immigrants and use model-based clustering to understand the assimilation of a particular case of first-generation immigrants: Chinese immigrants in a sparsely dispersed suburban/urban area (Raleigh-Durham). We identify four Chinese immigrant typologies, Chinese Friendship Networks, Socially Embedded, Undecided Newcomers, and Economically Integrated, which are distinguished simultaneously by their social networks and their demographic characteristics. In turn, we find different clusters show different patterns in assimilation indicators. These findings contribute to a growing literature that calls for more granular study of immigrant groups so we can better understand heterogeneity in their outcomes.

In Chapter 3, I study the limits of social networks for the immigrant job search. The idea that migrants draw on their networks to obtain employment upon arrival at their destination is central to the immigrant integration literature. However, despite the wealth of evidence on migrants' use of networks, little is known about when and why migrants are willing to help newcomers find work.

To study this, I deploy an online vignette experiment among Latin American immigrants to the United States. I find that immigrants are more likely to provide job search support to other immigrants from their home country but are less likely to lend support to newcomers that pose a reputational risk. I also find that tie strength is important – respondents in our sample are more likely to help a close friend than a stranger, which can help immigrants overcome the difficulties associated with a competitive labor market.

Dedication

To Tom.

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List of Abbreviations

ACS	American Community Survey
BBC	British Broadcasting Corporation
BIC	Bayesian Information Criteria
ChIRDU	Chinese Immigrants in the Raleigh-Durham Area Study
DANE	*Departamento Administrativo Nacional de Estadística*, or National Statistics Administration Department (Colombia)
DID	Difference-in-Differences
EU	European Union
GIHS	Great Integrated Household Survey
HS	High School
IOM	International Organization for Migration
LPA	Latent Profile Analysis
NA	North America
NSM	Network Sampling with Memory
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
OLS	Ordinary Least Squares
PCA	Principle Components Analysis
RDU	Raleigh-Durham Area
SATE	Sampled Average Treatment Effect

SD	Standard Deviation
SES	Socioeconomic Status
UAEMC	*Unidad Administrativa Migración Colombia* or Administrative Unit for Migration of Colombia
UK	United Kingdom
UNHCR	United Nations High Commissioner for Refugees
US	United States
USA	Unites States of America

Acknowledgements

Writing the bulk of this dissertation in a global pandemic, an international move, while planning a wedding and raising a puppy was not without its challenges. I am eternally appreciative to the people that were there for me along the way.

I am incredibly grateful to my entire dissertation committee. In particular, Giovanna Merli who was a mentor from day one. Thank you for your support and giving me the opportunity to learn-by-doing on ChiRDU as a first year and guiding me through this journey. I will miss the many dinners and conversations we had along the way.

Thank you to the rest of my committee for their continued support, Alex Volfovsky, Lisa Keister, Jim Moody and Marcos Rangel. Thank you to Alex Volfovsky for his patience and mentorship in statistics over the past four years and welcoming me into the Volfovsky lab. Thank you as well to Lisa A. Keister, from whom I learned a lot and always had kind words to say. Thank you to Ted Mouw for feedback and conversations on networks. Also a big thank you to Lisa Kukla for her support and lots of patience along the way.

I met lifelong friends at Duke and could not have completed this dissertation without them. Coffees and lunches and chats with Sarah Cross, Travis Dauwalter, Trung Tran, Harsh Parikh, Liann Tucker, Joe Quinn, and Adrienne Jones were invaluable. Thank you to M'Balou Camara for being my first Duke friend. Maria Nagawa has been

there for me since 2012(!) and our conversations about development have shaped my perspective. I am eternally grateful for the friendship of Allison Stolte (and Sam Speicher), who single-handedly got me though grad school in a pandemic and without whom this dissertation would surely not exist.

Outside of Duke, my family has shown support every step of the way, Cathy Fagan, François Le Barbenchon and Patrick Le Barbenchon.

Lastly, I dedicate this dissertation and my entire PhD to my husband Thomas Vargas. You are the love of my life. You were there for every moment of this dissertation. I'm just glad you got your PhD first so you could shine a light on the path for me. Words cannot describe what your support has meant for me over these years but I'm so glad we did it together.

Introduction

It is estimated that there are 272 million international migrants representing 3.5% of the global population, which is rising incrementally each year (IOM, 2020). The vast majority of these migrants, at least two thirds, uproot their lives in searching for labor opportunities abroad (IOM, 2020). Cumulative causation theory posits that migrant social networks are a catalyst to migration – having a connection at destination is an important predictor of migration (Massey, 2004). A related literature finds that migrants draw on their networks to obtain employment upon arrival at their destination (Aguilera, 2002, 2005; Ryan, 2011). Given the rising wave of international migration worldwide, the continued study of social networks is critical to understanding the lives and the incorporation of migrants in host communities.

This dissertation contributes to the growing body of literature on how migrant social networks shape their incorporation (or re-incorporation) processes. First, it examines how social capital can flow through network ties and allow migrants and return migrants to find work. Second, it links indicators of assimilation like employment, income and satisfaction with life to immigrant social network composition. Third, it studies how environments like the labor market context or availability of co-ethnic ties may affect how networks facilitate or harm incorporation.

Chapter 1 *Will friends and family still be there for you after you've left?*, adjudicates between two currents of migration research: those who say immigrants hold on to their networks when they are abroad, and those who argue that networks get severed after a migration experience. While it is widely acknowledged that immigrants use their social networks (friends, family and colleagues) to find a job upon arrival to their destination country, there is little evidence on how return migrants find jobs upon their return to their home country, one of the main pillars of re-integration. Whether or not they have networks available to them upon return, is thus crucial for understanding return migrants' experience. This chapter draws on data from two years of Colombian nationally representative surveys conducted in 2016 and 2017. I use a difference-in-differences approach and exploit a mass deportation event of Colombian migrants from Venezuela in 2015 which prompted a wave of return-migrants. I show that return migrants are more likely to draw on social networks in their search than never migrants, and that this is potentially due to inability to find jobs through other means. I also find evidence that jobs found through networks for return migrants may be lower quality than jobs found through other means. This paper makes an important contribution to help settle the debate on migrant networks by providing evidence that migrants maintain their networks while abroad and capitalizes on the relative paucity of existing work on return migration.

Chapter 2, *Identifying Immigrant Typologies through Networks*, is joint work with Giovanna Merli and Ted Mouw. In this chapter, we study how four of the dominant assimilation frameworks combine and overlap to explain the assimilation process of newer immigrant groups. Early works saw immigrant integration as a one-sided process of adaptation to the host country (Alba and Nee 1997). However, more recent conceptions of immigrant assimilation have emphasized the role of both immigrants and local hosts in their in the process of integration (Alba and Nee 1997; Zhou 1997; Portes and Rumbaut 2001). Among these, assimilation theory, segmented assimilation theory, transnationalism, and social networks theories have all been advanced to explain the process of immigrant integration as well as heterogeneity in immigrant outcomes in the host country. Importantly, these theories have highlighted the fact that immigrants with different characteristics and migration histories may have different experiences with assimilation to the host culture. However, it is less clear how these theories explain the assimilation process of recent cohorts of immigrants, especially those moving to new areas of destination in the U.S.

This paper investigates these questions in the context of Chinese immigrants in the U.S. South. We use a novel data set that we collected between March 2018 and January 2019 on over 500 Chinese immigrants to the Raleigh-Durham area. This data includes personal network surveys which include respondent ties to local Chinese immigrants, local non-Chinese born individuals, and Chinese-born individuals around the world. We then deploy finite Gaussian mixture models to detect clusters of immigrants with similar network structures and categorize respondents into groups. We identify four immigrant typologies in our sample: Chinese Friendship Networks, Socially Embedded, Undecided Newcomers, and Economically Integrated.

We find that these clusters are associated with important indicators of assimilation: satisfaction with life at destination, national identification, employment, and income. This chapter contributes to a growing body of literature that examines heterogeneity in migrant experience and outcomes within migrant groups (Drouhot & Garip, 2021). We conclude that no one assimilation framework accurately captures the migration experience of Chinese immigrants in the Raleigh-Durham Area. Instead, multiple theories are examined simultaneously to explain our findings. I led the analysis and writing of this chapter, the data collection was led by Giovanna Merli and Ted Mouw.

Chapter 3, *To Help… Or Not to Help?*, studies when and under what conditions migrants are willing to help newcomers find work. Is solidarity with fellow migrants the only factor individuals consider when helping a newcomer? What underlies a decision not to provide help to a fellow immigrant? My point of departure is that the notion that there is always intra-ethnic support in migrant communities is an assumption that is not well-supported. For example, immigrant provision of help to other newcomers may depend on perceived status (Portes & Shafer, 2007), perceived reputation (Smith, 2005), or whether there is competition for jobs (Ryan et al., 2008).

To better understand the underlying factors that contribute to the decision about whether to refer a fellow migrant for a job, I use a factorial experiment, consisting of two hypothetical scenarios that I express with vignettes. The first vignette presents a reputational risk scenario and the second presents a scenario in a competitive labor market. I run this experiment online, on a sample of Latin American immigrants to the USA and a sample of Latin American immigrants in the Raleigh-Durham area.

I find evidence that when a candidate poses a reputational risk to their fellow migrant referrer, they are significantly less likely to receive help in applying or a referral for the job. I also show that in a job shortage, immigrants are more likely to help close friends than strangers. These findings contribute to the literature on social networks and job searching among immigrants by highlighting that networks can be both a boon and a hindrance to newcomer incorporation.

1. Will Friends and Family Still Be There for You After You've Left?

1.1 Introduction

Scholars of migration have increasingly turned their attention to an often-neglected step in the migration process, return migration to one's home country. In this paper, I will focus on return migrants, individuals who have returned to their country of origin after experiencing a migration event. There is continued debate in the return migration literature about the resources available to return migrants as they seek reintegration to their communities of origin. There is some evidence that migrants lose their connections during their time abroad, making it difficult to draw on their networks for support upon return (Wahba and Zenou 2012; Waldinger 2015), others show that migrants maintain connections with their home country while they are abroad which would mean these networks are available to help them when they return home (Portes, Guarnizo, and Landolt 1999). Furthermore, when migrants leave their destination country in a hurry, like in the case of a forced removal, they may not have enough time to mobilize the resources necessary to smooth their reintegration. In this case, they might be obliged to rely on friends and family in their home country to access information and resources for their reincorporation (Cassarino 2004). This paper seeks to adjudicate between these two currents of return migration research and examines whether returnees use their social networks to find a job upon return from another country, to understand how local social capital may affect the reintegration process.

Migration is an inherently cyclical process, with anywhere from 20% to 50% of migrants leaving their host countries within a decade of arrival, and either returning home or moving to a different country (Dustmann and Görlach 2016). For example, from 2010 to 2015, around 70% of international migration in South America was to other countries in the same region, while an improving economy coupled with difficult conditions abroad has meant growing numbers of inter-regional return migrants coming back to South America (IOM 2018).

The reintegration of return migrants has garnered particular attention over the past couple of decades (Hagan and Thomas Wassink 2020), with many noting that forced return migrants face unique reintegration patterns (Arowolo 2000; David 2017). Finding work is one of the most important tenets of reintegration, as jobs provide economic resources, which may be in short supply for return migrants (Anderson 2015; Brotherton and Barrios 2011; Cassarino 2004; David 2017; Golash-Boza 2015), as well as social and emotional stability (Hagan, Castro, and Rodriguez 2009). Despite a wealth of evidence on the employment outcomes and occupational mobility of return migrants (Carletto and Kilic 2011; Cobo, Giorguli, and Alba 2010; Lindstrom 2013; Mezger Kveder and Flahaux 2013), the literature exposes vast heterogeneity in labor market outcomes for return migrants, from favorable job conditions and upward occupational mobility (Barrett and O'Connell 2000; Carletto and Kilic 2011; Mezger Kveder and Flahaux 2013), to low-quality work as a result of downward mobility (Lindstrom 2013). There is scant evidence, however, on the methods employed by return migrants to find work. While many acknowledge there are differences in job outcomes based on migrant characteristics or migration experience (Cobo et al. 2010; Lindstrom 2013; Mezger Kveder and Flahaux 2013), understanding job search strategies can help us better understand a potential driver of these differences. For example, if certain job search strategies are more likely to lead to high quality jobs than others (Diaz 2012), this may help explain some of the variation in outcomes seen across studies.

In this paper, I focus on the relationship between being a return migrant and using social contacts to find a job. I define return migrant as an individual who has lived abroad and has since returned to their home country. I have three objectives. First, I aim to establish whether return migrants and forced return migrants use their social capital to find work upon return. Second, I try to disentangle the potential mechanisms underlying this result. Third, I seek to understand the quality of jobs found through networks, and whether they are deemed satisfactory by the return migrants that hold them. I use two years of data from a nationally representative survey of Colombians, which includes rich detail on their job search and employment history, and questions on return migration. I find that return migrants are more likely to use friends, family or colleagues to find a job than non-migrants. My results also indicate that returnees are unable to find work through other channels, pushing them towards using networks and that these jobs are lower quality on average. These findings contribute to research on return migrant social capital, labor market outcomes for return migrants, and their impacts on integration and overall well-being.

1.1.2 Context: Colombia

Colombia presents an interesting case study of the relationship between return migration and job searching. Firstly, it is the country with the highest number of internally displaced persons in the world, with 7.2 million residents displaced due to conflict (IOM 2018). From 1990 to 2007, over 40,000 individuals were murdered due to armed conflict which raged between the Colombian state, paramilitary and two principal guerilla groups (UNHCR 2007). Secondly, it has seen high levels of out-migration to neighboring countries, mainly Venezuela, in pursuit of economic opportunity and increased stability. An estimated 1 million Colombians were living in Venezuela at the beginning of 2015 (IOM 2018). Colombian immigrants in Venezuela tend to live in border regions, experience poverty and housing insecurity, and hold informal, unstable jobs (UNHCR 2007). However, since around 2013, Venezuela has experienced an increasingly devastating economic, political and humanitarian crisis. In early 2015, this crisis prompted waves of out-migration by both foreigners and citizens of Venezuela, as oil prices dropped, and food and other basic necessities became scarce. During this time, Colombians began to return home in large numbers to escape the crisis (Kurmanaev and Medina 2015). Return migration was accelerated in August 2015 and the months following, when President Maduro expelled 2000 Colombians from border cities, and the ensuing fear and chaos prompted tens of thousands of others to flee Venezuela (OCHA 2015). Considering the ongoing crisis, return migrant integration is likely to take a spotlight in Colombian migration policy in the coming years (IOM 2018).

1.2 Theoretical Framework

1.2.1 Social Capital

The social capital literature provides a useful starting point for understanding a return migrant job search. Individuals often draw on their social network (friends, family and acquaintances) in order to access information and resources that may help them in their search (Castilla, Lan, and Rissing 2013; Granovetter 1973; Lin 2008; Lin, Cook, and Burt 2001; Marsden and Gorman 2001). Indeed, social ties may offer information about job opportunities even when the individual is not actively looking for work (McDonald and Glen H. Elder 2006).

There is evidence that pursuing employment using networks, or social capital, is more likely to result in a hire than applying directly (Fernandez, Castilla, and Moore 2000; Pedulla and Pager 2019; Petersen, Saporta, and Seidel 2000), in part because candidates with connections at the firm have insider knowledge allowing them to put forth stronger applications (Fernandez et al. 2000). Those who use their contacts to find jobs can often find better-suited employment for their skills, find out about unadvertised opportunities, or find employment more quickly (Aguilera 2002; Calvó-Armengol and Jackson 2004; Montgomery 1991).

However, the use of social capital to find work may not result in higher occupational status or increased wages. Job searches using contacts do not appear to yield higher salaries (Diaz 2012; Elliott 2000; Green, Tigges, and Diaz 1999), and social capital may be more beneficial for white than black individuals (McDonald and Day 2010; Pedulla and Pager 2019; Smith 2005). Indeed, because wage or prestige outcomes may be correlated with an individual's network, it is unclear whether there are causal links between networks and job outcomes, or whether these are merely correlational (Mouw 2003).

Research on immigrant populations shows similar trends. Access to social networks makes immigrants more likely to land a job (Greenwell, Valdez, and DaVanzo 1997), in part by providing information, and steering them towards more desirable, formal, work (Aguilera and Massey 2003). However, the evidence on whether those jobs are high quality is mixed. For Puerto Rican women in the US, social capital (defined as living with other Puerto Ricans and participating in organizations) is positively correlated with income (Aguilera 2005). However, in rural areas where sparser networks dominate, Mexican migrants found better-paying jobs when they did not make use of networks (Pfeffer and Parra 2009). There is no evidence, however, on the use of social capital among *return* migrants, who present different challenges to finding work than immigrants.

1.2.2 Social Networks and Migration

Whether migrants can draw on their social capital to find work upon return will depend on the extent to which those networks are available to them (de Haas, Fokkema, and Fihri 2015). The neoclassical economic view of migration posits that immigrants will try to stay in their destination country for as long as possible, so as to maximize the returns to migration (Constant and Massey 2002). In this framework, maintaining ties to one's home country is costly, as it interferes with integration and earning maximization abroad (Constant and Massey 2002).

Along these lines, Waldinger (2015) argues that immigrants will lose ties to their home country because technology and travel home are costly, and legal restrictions can make visits difficult, which can ultimately strain the immigrant-home relationship. He argues that those who have left have *chosen* to immigrate to their new country for a better life. As they adapt to and benefit from their new environment, ties to home tend to shrink and eventually wither. Indeed, it has been shown that upon return, migrants may find their friends and connections have moved on (Tannenbaum 2007). How returnees are received by friends and family depends on context (Arowolo 2000), but some returnees face stigma about a "failed migration" which can make it difficult to rely on family, who may repudiate them upon return (Dingeman 2018; Golash-Boza 2015; Schuster and Majidi 2013, 2015).

In contrast, proponents of transnationalism theory posit that immigrants maintain connections to their home countries of origin and reject the notion of cut ties to home and uni-directional migration intentions (Portes, Guarnizo, and Haller 2002; Portes et al. 1999). It appears that immigrants maintain strong ties with their homeland and these ties can help explain their decision-making and integration (Beauchemin 2014; Mouw et al. 2014; Verdery et al. 2018). Under the assumptions of transnationalism, immigrants may nurture relationships with their ties at home, as these can, in some instances, contribute to immigrant success abroad (Portes et al. 2002). In these cases, return migrants would have rich networks to draw on upon their return to help them find work.

To explain reintegration outcomes, Cassarino (2004) proposes a framework that emphasizes the level of "preparedness" of the return migrant, theorizing that migrants who have less time to accumulate resources and to prepare for their return home, like forced migrants, will have fewer avenues for reintegration and will be obliged to rely on existing family and friend ties. Per Cassarino, migrants not only maintain their ties as part of their migration process, but also fall back on them when they are under-resourced upon return. Studies of deported immigrants underline the importance of friends and family for helping migrants find work upon return. There is qualitative evidence that Salvadorian return migrants who are deported from the US use their pre-migration networks to find work (Dingeman 2018). Afghans deported to their home country from Europe have relied on family support for housing and other resources to reintegrate (Schuster and Majidi 2013, 2015). Deported immigrants will often have to rely on family for support and resources, even when they don't want to (Golash-Boza 2015). Given that, due to the geo-political context of their migration event, Colombian return migrants are likely to be lower resource and on the lower side of preparedness, I elaborate the following hypothesis:

Hypothesis 1: Return migrants, and particularly unprepared return migrants, are more likely to use networks to find their job than never migrants.

If Hypothesis 1 holds, we then may wonder *why* return migrants are more likely to use social networks than their non-migrant counterparts. On one hand, return migrants may have a preference for using networks. We know that some immigrants use networks to find jobs when they are abroad (Aguilera 2002; Ryan 2011) and that migrants learn behaviors in their destination country which they bring home (Bertoli and Marchetta 2015; Tuccio and Wahba 2018). We could conclude that return migrants might "learn" a networks-based job search behavior, and then apply this method when they return, thus exhibiting a preference for this method.

On the other hand, reliance on networks may be return migrants' only option when they find it difficult to find a job for two reasons: (1) local employers may not recognize the work experience or credentials gained abroad, especially when job types or industries abroad are not the same as those required locally (Lindstrom 2013); (2)

longer time abroad creates distance between returnees and local labor markets, meaning that return migrants' skills may be mis-aligned with what employers need (Cobo et al. 2010; Lindstrom 2013). Return migrant narratives also emphasize a reliance on family as a last- resort, or as undesirable (Dingeman 2018; Golash-Boza 2015), which may be especially true for migrants experiencing an unprepared return (Cassarino 2004). This leads to the formulation of the following hypothesis:

Hypothesis 2: Return migrants experience barriers to finding jobs through non-network channels, and thus are pushed towards using networks as a last resort.

If Hypothesis 2 holds, I expect to see that unemployed searchers mainly use a job search method *other* than networks to search, but that those who found a job, found it through networks.

There is also evidence that immigrants can draw on household ties to find work in new environments (Aguilera 2005), which may mean that household size can influence returnees' likelihood of using networks to find work. Therefore, I will also test whether return migrants have larger households which may signal larger networks.

1.2.3 Return Migration and Occupations

There is continued debate in the literature on the occupational mobility of return migrants. While some studies find a positive effect of return migration on occupational or income mobility (El-Mallakh and Wahba 2021; Wahba 2015) others find mixed results (Carletto and Kilic 2011; Cobo et al. 2010; Mezger Kveder and Flahaux 2013; Piracha and

Vadean 2010), or even predominately downward occupational mobility (Lindstrom 2013).

Multiple explanations have been advanced for this range of findings. Carletto and Kilic (2011) show that migrants with more human capital will seek destinations that allow them to work in higher skilled work, and thus upskill and increase their occupational mobility upon return. Cobo et al., (2010) show that some origin countries have more opportunities for occupational mobility than others, which can facilitate re-integration and climbing the occupational ladder upon return.

Multiple authors focus on occupational choice to understand migrant labor market integration. Mezger Kveder and Flahaux (2013) apply mixed methods in Senegal and find that self-employment seems to be a choice of last resort for immigrants that could not find wage employment, which explains the high proportion of self-employed returnees. Piracha and Vadean (2010) come to a similar conclusion, finding that self-employed return migrants earn less than wage earners on average. In addition, education and "preparedness" appear to be important factors in determining mobility (Mezger Kveder and Flahaux 2013)– with less prepared returnees facing worse occupational mobility.

While I cannot directly test the effect of return migration on occupational mobility, because I do not have occupations pre- and post- migration, I will attempt to explore whether job search method can partially explain the *quality* of jobs obtained by return migrants and forced return migrants. It could be that if return migrants are lower status than non- return migrants, their use of networks may be beneficial in helping them find a job, but will not necessarily lead to quality jobs (Mouw 2003; Pedulla and Pager 2019; Smith 2005). While migrants are typically higher status than peers they leave behind (Hatton, Williamson, and Williamson 1998), return migrants, especially forced return migrants, may be perceived as failures or criminals (Anderson 2015; Dingeman 2018; Golash-Boza 2015). Therefore:

Hypothesis 3: Jobs that return migrants find using networks are likely to be lower quality than those found using other means.

1.3 Data and Descriptive Statistics

The main estimation strategy focuses on migrants who returned in 2015, during a wave of return migration from Venezuela to Colombia. To capture these migrants, I use data from the 2016 and 2017 Great Integrated Household Survey. These data are collected monthly in Colombia in a rolling sample cross-sectional survey, which is nationally representative of the population of Colombia. I combine the 24 months from the 2016 and 2017 data (DANE 2016, 2017). These data years are chosen because they include a granular breakdown of “reason for return”, which is absent from the 2015 survey. I start with a total sample of 1,546,105, with 778,238 respondents surveyed in 2016 and 767,867 in 2017. After excluding foreign-born immigrants, I obtain a sample of 1,531,463 Colombia-born respondents. The main analytic sample of 1,526,210 also excludes return migrants from countries other than Venezuela for the sake of clarity, though they are included in robustness checks, and this choice does not affect substantive results. Around 0.6 % of my analytical sample are return migrants from Venezuela (8,704 individuals). While this is a small proportion, the overall sample size has enough power to detect heterogeneous effects. The breakdown of this sample by year and return migrant status is presented in Table 1, which also shows the final N in each category. In cases where there was missing data on independent or dependent variables, I performed listwise omission of observations from the model. In Table 5, for example, only 522 returnees of 1696 were employed and had complete data on all independent and dependent variables, income and job satisfaction having more missingness than demographic or household controls. This dataset is particularly apt for the study of return migration and job searching for three reasons. First, it contains survey questions on the use of social networks in the individual's job search strategy for both employed and unemployed respondents. To my knowledge, this is the only nationally representative survey that contains both of these variables. Second, it has a large sample size which is important for capturing heterogeneous effects. Third, respondents were administered job history questions (current job or current spell of unemployment, previous spell of unemployment and previous job) and migration history questions, limited to their most recent international migration experience.

1.3.1 Measures

1.3.1.1 Return Migration

Return Migrant from Venezuela - The main independent variable is a binary indicating whether or not the individual is a return immigrant from Venezuela in the previous year or 5 years. This draws on a survey question that asks, "Where did you live 1 year ago" or "Where did you live 5 years ago", with a list of countries to choose from, including Venezuela. There may be concerns, however, that immigrants time their return in tandem with their job search strategy, such that their return is driven by their job search method, and not the reverse. I propose two additional measures of return migration that would suggest an "unprepared" return, not driven by job search.

Return Migrant for "Exogenous" Reason - One estimation strategy relies on understanding the job search behavior of migrants that returned in a hurry, making it unlikely that their return is driven by their job search. For this, I utilize a survey question that asks, "What is the main reason for which you moved within the past 12 months?". I deem it to be an exogenous shock if they answer either (1) Threats or risk to your life or physical integrity due to armed conflict; (2) Threats or risk to your life or physical integrity not due to armed conflict; (3) Natural disasters. There is an option to select "work" as a reason for return to Colombia and I use this as a robustness check (see Robustness Check section).

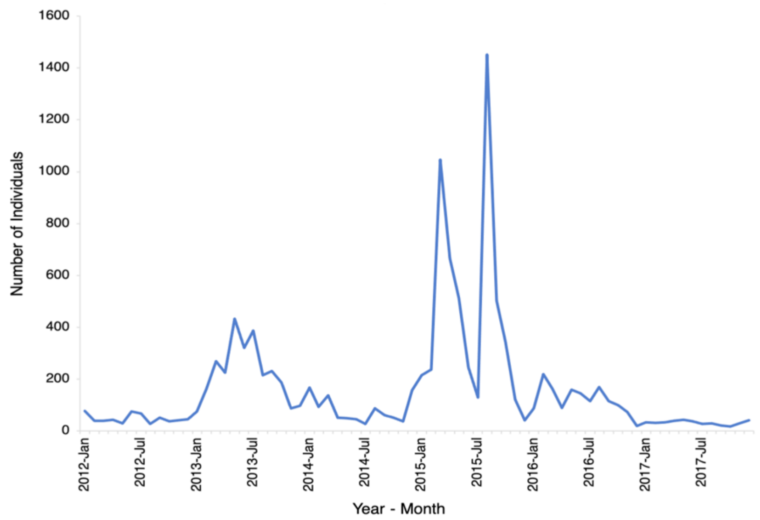

Figure 1: Number of Deportations of Colombians Arriving From Venezuela per Month from 2012-2017

Return migrant in 2015 - Another part of my estimation strategy relies on a differences-in-differences approach to capture migrants who returned to Colombia from Venezuela and found a job in 2015. On August 21st, 2015, the Venezuelan government reacted to the shooting of three Venezuelan soldiers by declaring a state of emergency along the Colombian-Venezuelan border (BBC News 2016). This ultimately led to the deportation of nearly 2,000 Colombians and return under duress of around 22,000 Colombians during the month following the incident (OCHA 2015). This was partially an electoral strategy to clamp down on alleged oil smugglers along the border, even though the deportations and state of emergency was not declared in the locations where this activity was most prevalent (Washington Post 2015). Earlier in the year, strife was mounting in Venezuela and deportations and mass migration movements of Colombians back to Colombia were already underway. Indeed, the available data reflect these changes. Official Colombian migration data shows a spike of deportations or forced returns around March and September of 2015 (UAEMC 2012-2017). In Figure 1, I show deportation levels from Colombian administrative data. The spike in deportations follows the same trend across all age groups with two large spikes in 2015. In the GIHS survey data, I find returnees are over eight times more likely to report they returned due to a threat to their lives not due to armed conflict if they are estimated to have returned in 2015, than if they returned any other year in my sample.

Table 1: Summary Statistics for Full and Analytic Sample

	2016		2017		Total	
	Never Migrants	Return Migrants	Never Migrants	Return Migrants	Never Migrants	Return Migrants
Employment						
employed	0.89	0.83	0.90	0.85	0.90	0.84
	(0.31)	(0.38)	(0.31)	(0.36)	(0.31)	(0.37)
unemployed	0.11	0.17	0.10	0.15	0.10	0.16
	(0.31)	(0.38)	(0.31)	(0.36)	(0.31)	(0.37)
inactive	0.33	0.24	0.33	0.22	0.33	0.23
	(0.47)	(0.43)	(0.47)	(0.41)	(0.47)	(0.42)
Job Type						
Employee	0.42	0.26	0.42	0.29	0.42	0.27
	(0.49)	(0.44)	(0.49)	(0.45)	(0.49)	(0.45)
Domestic worker	0.03	0.06	0.03	0.07	0.03	0.06
	(0.18)	(0.23)	(0.18)	(0.25)	(0.18)	(0.24)
Self-employed	0.46	0.62	0.46	0.58	0.46	0.60
	(0.50)	(0.48)	(0.50)	(0.49)	(0.50)	(0.49)
Manager	0.03	0.01	0.04	0.02	0.04	0.01
	(0.18)	(0.12)	(0.19)	(0.12)	(0.19)	(0.12)
Unpaid worker	0.04	0.03	0.04	0.04	0.04	0.04
	(0.19)	(0.18)	(0.19)	(0.20)	(0.19)	(0.19)
Day laborer	0.01	0.01	0.01	0.01	0.01	0.01
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)
Other	0.00	0.00	0.00	0.00	0.00	0.00
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
Observations	582744	3404	575615	4093	1158359	7497

Descriptive Characteristics of Analytical Sample						
Dependent Var						
Used network	0.63	0.82	0.63	0.79	0.63	0.80
	(0.48)	(0.39)	(0.48)	(0.41)	(0.48)	(0.40)
Demographics						
Female	0.48	0.43	0.48	0.44	0.48	0.44
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Age (years)	36.62	34.54	36.92	36.49	36.77	35.68
	(12.42)	(11.08)	(12.49)	(11.15)	(12.45)	(11.16)
Married	0.22	0.11	0.22	0.13	0.22	0.12
	(0.41)	(0.31)	(0.41)	(0.34)	(0.41)	(0.33)
Education						
None	0.01	0.03	0.01	0.02	0.01	0.03
	(0.12)	(0.17)	(0.12)	(0.15)	(0.12)	(0.16)
Highschool or less	0.55	0.78	0.55	0.83	0.55	0.81
	(0.50)	(0.41)	(0.50)	(0.38)	(0.50)	(0.39)
At least tertiary	0.44	0.18	0.44	0.15	0.44	0.17
	(0.50)	(0.39)	(0.50)	(0.36)	(0.50)	(0.37)
Household						
Household Size	4.09	4.18	4.04	3.73	4.06	3.92
	(1.98)	(2.37)	(1.97)	(2.65)	(1.98)	(2.55)
Job Characteristics						
Income (in 000s pesos)	10.95	7.73	11.45	8.09	11.19	7.94
	(11.97)	(5.24)	(12.43)	(5.26)	(12.20)	(5.26)
Industry						
Raw Materials	0.06	0.08	0.06	0.06	0.06	0.07
	(0.23)	(0.27)	(0.24)	(0.25)	(0.24)	(0.26)
Manufacturing	0.19	0.23	0.19	0.21	0.19	0.22
	(0.39)	(0.42)	(0.39)	(0.40)	(0.39)	(0.41)
Retail	0.12	0.13	0.12	0.15	0.12	0.14
	(0.32)	(0.34)	(0.33)	(0.36)	(0.32)	(0.35)
Commercial services	0.29	0.29	0.29	0.31	0.29	0.30
	(0.45)	(0.45)	(0.45)	(0.46)	(0.45)	(0.46)
Health and Education	0.24	0.07	0.23	0.06	0.23	0.06
	(0.42)	(0.26)	(0.42)	(0.23)	(0.42)	(0.24)
Domestic services	0.11	0.19	0.11	0.21	0.11	0.21
	(0.31)	(0.40)	(0.31)	(0.41)	(0.31)	(0.40)
International	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00
Quality Index	7.51	6.42	7.59	6.44	7.55	6.43
	(2.23)	(2.33)	(2.17)	(2.30)	(2.20)	(2.31)
Observations	163685	703	161488	993	325173	1696

Note: Values are proportions unless noted otherwise

1.3.1.2 Dependent Variables

For my dependent variable, I use a survey question on how individuals found their current job, with six possible mutually exclusive answer categories. I create a variable coded 1 if the individual responded, "Asked for help from family, friends or colleagues" and 0 otherwise. This question is answered by all individuals who report they are employed, and not self-employed. There is a risk that I am capturing the returnee's second or even third job after return. In Table 2, the return migrants are restricted to those who returned in the past year, where I believe it is most likely I am capturing the returnee's first job after return. For the difference-in-differences estimates, I consider all return migrants as treated, whether they arrived in the past year or 5 years. As a robustness check, I consider only returnees who returned in the past year as treated. I find only standard errors are sensitive to this change, which is attributable, at least in part, to the smaller sample size.

Another set of dependent variables that I use are for estimating results in Table 5, comparing the job outcomes of returnees who used networks to returnees who did not. I examine three job types: (1) Salaried Worker, (2) Domestic Worker or (3) Day Laborer; and seven industries: (1) Raw Materials, (2) Manufacturing, (3) Retail, (4) Commercial Services, (5) Health and Education, (6) Domestic Services, or (7) International Sector. Lastly, I construct an index, "Quality Index" where there is a point given if the individual reports any of the following quality indicators, up to a maximum of 9: (1) whether or not there is paid vacation, (2) a holiday bonus, (3) paid unemployment, (4) whether it meets the terms of the contract, (5) whether the hours are sufficient, (6) whether the job is satisfactory, (7) whether compensation is satisfactory, (8) job is stable, and (9) job is compatible with family obligations. I also look income as a separate measure of job quality.

1.3.1.3 Control variables

In addition to the main dependent and independent variables, I include a number of control variables in the models. Month and year that job was found is a categorical variable which gives the month (e.g., April) and year (e.g., 2015) in which the individual found their job. That way, we can compare individuals who began their work and ended their job search at around the same time. We also include controls for the 24 Colombian departments surveyed, which allows us to control for geography. Age is measured in years. Female is a dummy variable for female with male as reference category. Education is measured in binary categories (No education, primary and middle school and tertiary and above). Married is a dummy variable for whether respondent is married at time of survey. It is important to note that all variables are from time of survey, which is post-return for returnees.

In the top of Table 1, we see descriptive statistics from the full samples of individuals in the GIHS. A slightly higher proportion of never migrants are employed than returnees from Venezuela, and there are proportionally more returnees unemployed, and fewer inactive, than never migrants. Of those who are employed, return migrants are more likely to be self-employed, as shown in Mezger Kveder and Flahaux (2013) and Piracha and Vadean (2010), and less likely to be employees.

The bottom part of Table 1 shows individuals that are employed and not self-employed, as these are individuals who answer the survey question for my dependent variable: how they found their most recent job. We see that returnees from Venezuela are more likely to have used networks (as expected in Hypothesis 1), are more likely to be male, and more likely to have only a high school education or less, than never migrants. In terms of their jobs, we find that they are less likely to be in Health and Education services, and more likely to be in Domestic Services. We also show that returnees in our sample have a Quality Index score on average 1 point less than those of never migrants. This already lends some preliminary evidence in support of Hypothesis 3, that returnees have lower quality jobs upon return.

1.4 Return Migrants Use Networks to Find a Job Upon Return

1.4.1 OLS Estimation

1.4.1.1 Methods

To test Hypothesis 1, return migrants are more likely to use networks to find their job than never migrants, I employ OLS linear probability models. I estimate the following equation:

$$Y_{ij} = \alpha + \beta_1 r_{ij} + \beta_2 \mathbf{X}_{ij} + \delta_i + \gamma_j + E_{ij} \qquad (1.1)$$

Where Y is a binary outcome that takes a 1 if individuals used friends or family to find their job, 0 otherwise, indexed by month and year job was found i and Colombian department j. α is a constant. r is an independent variable that is constructed in two different ways, described in the data section: (1) Having returned from Venezuela in the past year, (2) Having returned from Venezuela in the past year for an "exogenous" reason. **X** is a vector of demographic covariates which are: gender, age, marital status, education, and household size. δ is a fixed effect for month job was found, and γ is a fixed effect for one of 24 surveyed departments.

1.4.1.2 Results

Table 2 shows results from these regressions. I find a positive, significant relationship between being a return migrant and use of networks in the job search. Columns (3) and (6) show results with a full set of controls and fixed effects for the month-year the job was obtained, and Colombian department. I find that returnees from Venezuela who returned to Colombia in the past year are 11% more likely ($p < 0.01$) to have used social networks to find their most recent job than never migrants. When we restrict our independent variable of interest to those who returned due to a random shock, we find they are 6% more likely ($p < 0.1$) to use networks to find a job.

These findings are consistent with the idea that return migrants are more likely to use networks to find their job than never migrants (H1). This is consistent with the idea that migrants maintain their networks when they move abroad, and thus have access to them when they return, in line with network-based perspectives from the transnationalism literature (Beauchemin 2014; Mouw 2003; Portes et al. 2002, 1999; Verdery et al. 2018).

Of our control variables, education has the strongest impact on the use of networks; more educated individuals are less likely to use social networks to find work than those without any education, net of our other independent variables. This echoes findings from the general population in Colombia that more educated workers are less likely to use networks to find a job .

1.4.2 Difference-in-Differences Estimates

1.4.2.1 Methods

Despite care taken to restrict my independent variable to those that returned for non-employment reasons, concerns may remain that there is an omitted variable bias or endogenous relationship between being a return migrant and job search strategies. In order to address this potential source of bias, I model the relationship between return and use of networks in a difference-in-differences (DID) framework. I exploit a mass return migration event occurring between January through December of 2015 (see Figure 1). Following Cassarino (2004), I expect that an influx of unprepared returnees, returning due to forced migration or leaving due to distress, to lead to an increased use of networks to find work. DID allows me to examine this shift by netting out the trend in network use of never migrants, who we expect present a counterfactual trend for returnees.

Table 2: OLS Models of Relationship Between Use of Networks to Find Job and Being a Recent Returnee

	(1)	(2)	(3)	(4)	(5)	(6)
Ret. from V. in past year	0.16***	0.10***	0.11***			
	(0.02)	(0.02)	(0.02)			
Ret. due to random shock				0.11***	0.06+	0.06+
				(0.03)	(0.03)	(0.03)
Age (years)	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.02***	0.02***	0.02***	-0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	-0.06***	-0.03***	-0.03***	-0.06***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education						
No education		Ref.	Ref.		Ref.	Ref.
HS or less		-0.10***	-0.10***		-0.10***	-0.10***
		(0.01)	(0.01)		(0.01)	(0.01)
Tertiary or more		-0.34***	-0.34***		-0.34***	-0.34***
		(0.01)	(0.01)		(0.01)	(0.01)
Household						
Household Size			0.00***		0.00***	0.00***
			(0.00)		(0.00)	(0.00)
Constant	0.86***	1.09***	1.07***	0.86***	1.07***	1.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Month f.e.	YES	YES	YES	YES	YES	YES
Department f.e.	YES	YES	YES	YES	YES	YES
Observations	189671	189654	189654	189671	189654	189654

Notes: Coefficients from linear probability models. Standard errors in parentheses. Ret. from V. in past year indicates an individual in the sample returned from Venezuela in the past year. Ret. due to random shock indicates individual returned from Venezuela in the past year for an "exogenous" reason, see text for details. Base category for those variables are never migrants. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

I estimate the following equation:

$$Y_{ij} = \alpha + \beta_1 T_{ij} + \beta_2 t_i + \beta_3(T_{ij} * t_i) + \beta_4 \mathbf{X}_{ij} + \delta_i + \gamma_j + E_{ij}, \qquad (1.2)$$

Where Y is a binary outcome that takes a 1 if individuals used friends or family to find their job, 0 otherwise, indexed by month job was found i and Colombian department j. α is a constant. T is an independent variable that indicates whether and individual is a returnee from Venezuela. t_i is an indicator variable for the treatment period (deportation and forced return shock) from January 2015 to December 2015. Individuals receive a 1 if they found their job in this interval, and a 0 otherwise. While the average time to find a job for returnees is 3.6 months, the median is under a month - a large portion of deportees and forced returnees are finding jobs shortly after they arrive. Therefore, the assumption of the shock occurring in 2015 and the job search occurring during that period seems reasonable.

X is a vector of demographic covariates which are: gender, age, marital status, education, and household size. δ is a fixed effect for month job was found, and γ is a fixed effect for one of 24 surveyed departments. I exclude months and years before January 2014, because the pre-period trend is extremely sparse, and thus unreliable for this estimation strategy. I am estimating β_3, the coefficient on the interaction between the time shock and the "treated" return migrant group.

This estimation strategy typically relies on the assumption of parallel trends, that is, that monthly trends in the use of networks grew (or fell) at the same rate for return migrants and never-migrants. I present Figure 2, which shows this trend. It is important to note that I restrict the pre-trends data to the 12 months of 2014. This is because data for return migrants before January 2014 is sparse, leading to highly variable and unreliable estimates. The scatter plot for 2014 is variable due to sample size, however the linear trend, and basis for the DID estimations, are comparable across both groups.

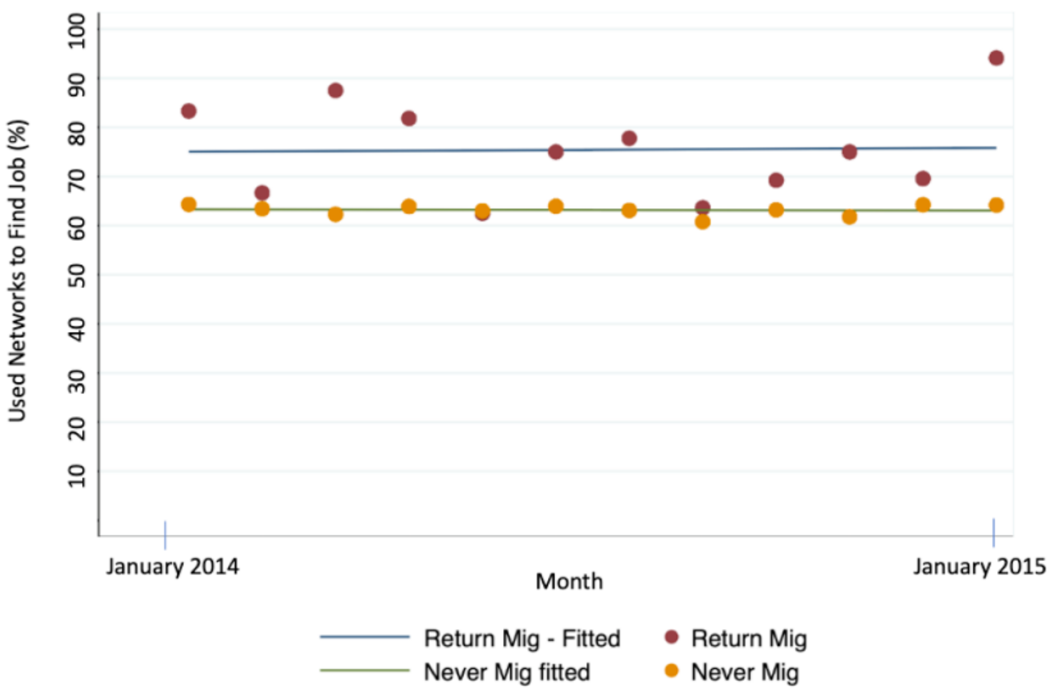

Figure 2: Proportion of Individuals in Returnee and Never Migrant Groups that Used Networks to Find Work

1.4.2.2 Results

Table 3: DID Models of Relationship Between Use of Networks to Find Job and Being a Recent Return Migrant

	(1)	(2)	(3)
2015	0.04***	0.03*	0.03*
	(0.01)	(0.01)	(0.01)
Return Migrant	0.10***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)
Return Mig * 2015	0.06*	0.06*	0.05*
	(0.02)	(0.02)	(0.02)
Age (years)	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
age2	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Female	-0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
Married	-0.06***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)
Education			
No education	REF	REF	REF
HS or less		-0.09***	-0.09***
		(0.01)	(0.01)
Tertiary or more		-0.34***	-0.33***
		(0.01)	(0.01)
Household			0.01***
Household size			
	0.89***	1.09***	(0.00)
Constant			1.06***
	(0.02)	(0.02)	(0.02)
Month f.e.	YES	YES	YES
Department f.e.	YES	YES	YES
Observations	192374	192357	192357

Notes: Coefficients from linear probability models. Standard errors in parentheses. Return Mig indicates an individual in the sample returned from Venezuela. 2015 indicates individual found their job in 2015, details in text. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household over age of 12 [verify exact age]. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

Table 3 shows results from the DID regression. The coefficients of interest are the interaction estimates for Return Migration and 2015. I find being a return migrant and finding a job in 2015 makes you 5% more likely to use networks in the specification with full controls ($p < 0.05$). This aligns with findings that deportees or forced migrants are more likely to use networks as a last resort than other type of return migrants. The magnitude of coefficients is also in the ballpark of estimates on all return migrants. For example, for the relationship between use of networks and returning due to random shock, I find a coefficient of 0.06, compared to 0.05 found in the DID estimates.

1.4.2.3 Robustness Checks

In order to verify that the DID results are not the result of a specification that *always* leads to positive effects, I conduct a placebo test where I apply the return migration "shock" to other years in our dataset (2014, 2016 and 2017) and verify the results. The results are shown in Table 16 in Appendix A. I see that, unlike our 2015 shock, none of the β_3 interaction coefficients are statistically significant for these placebo years, and in fact, show a negative relationship between β_3 and using networks to find a job. This indicates that returning and finding a job in 2015, during a time of duress, leads to a greater use of networks.

In addition to the DID strategy, I perform a number of sensitivity tests on both the original specifications and the DID specifications. These are available in Tables 17 and 18 in Appendix A. In the first test, in Table 17, Column (1), I restrict the independent variable to individuals who report that they returned in the past 5 years, but not 1 year. In Column (2), I include all returnees from Venezuela (5 years or 1 year). In Column (3), I include the full sample, meaning the control group for the main independent variable includes returnees from other countries and the "treatment" group is returnees from Venezuela in the past year. In Column (4), the control group is individuals who returned from the US or the EU and the "treatment" group is returnees from Venezuela in the past year. In Column (5), the control group is other immigrants who returned from neighboring countries (Panama, Ecuador, Peru) and the "treatment" group is returnees from Venezuela in the past year. In Column (6) I restrict the "treatment" group to returnees from Venezuela in the past year who returned due to their job. This could indicate a more extreme case of endogeneity, such that the return was caused by the job, and not the reverse. Lastly, in Column (7) I omit from the sample household members of returnees, because they may have unique job search due to the presence of returnees in their close network. For each of these specifications, I find a positive relationship between returning from Venezuela and using networks to find a job, with p-values of 0.05 or lower.

Lastly, I run all of these robustness checks in the DID framework (see Table 18). I find when I restrict the sample to include only those who returned in the past year, Column (1) models, the results are positive but no longer significant. This is likely due to the reduction in sample size. Similarly, restricting the control group to individuals returning from the US/EU (Column (4)) or restricting the treatment group to those who are returning due to their work (Column (6)), leads to results that are positive but not statistically significant. This is likely due to the reduction in sample size.

1.5 Return Migrants Use Networks as a Last Resort

1.5.1 Methods

In the previous sections I show that return migrants, especially those who return under conditions of duress due to instability or conflict, are more likely to use networks to find their job than never-migrants. It is unclear, however, what mechanism underlies this result. Some argue that returnees may use their networks to find work as a last resort, when they haven't been able to adequately prepare their return home (Cassarino, 2004). Others say migrants lose many of their network ties during their migration period (Waldinger, 2015b). In the latter case, reliance on networks would be a *preference* and not a necessity. Indeed, it is well known that migrants use networks to find jobs abroad (Aguilera, 2002), they may thus seek to use the same search method when they return home.

To test Hypothesis 2, that return migrants experience barriers to finding jobs through non- network channels and are pushed towards using networks as a last resort, I compare the job search strategies of unemployed individuals with those that found a job in the same month. If return migrants have a preference for using networks, I will find that unemployed returnees report using networks as their preferred job search mechanism and that employed returnees found their jobs through networks at the same rate. If instead, return migrants prefer *not* to use networks, I will find that unemployed returnees are *less* likely to be using networks as their preferred search method, but that employed returnees are more likely to have used networks to obtain their job because they used their networks as a last resort. This would show that unemployed individuals are mainly a job search method *other* than networks, but that those who are employed, found their job through their networks. The sample is restricted to returnees from Venezuela, either in the past year or five years. I estimate the following equation:

$$Y_{ij} = \alpha + \beta_1 m_{ij} + \beta_2 \mathbf{X}_{ij} + \delta_i + \gamma_j + E_{ij} \qquad (1.3)$$

Where Y is a binary outcome that takes a 1 if individuals used friends or family to find their job for employed individuals OR reported this was their main method of search for unemployed individuals. This is indexed by i for month job was found for employed individuals OR month survey was taken and search was underway for unemployed individuals, and by j for department. α is a constant. m_{ij} is our variable of interest which takes a 1 if the individual is employed and 0 if the individual is unemployed. $\mathbf{X}_{ij}$ is a vector of demographic covariates which are: gender, age, marital status, education, and household size. δ_i is a fixed effect for month job was found or month of search if individual is unemployed, and γ_j is a fixed effect for one of 24 Colombian departments. I exclude months and years before January 2012, because this is before return migrants have returned to Colombia in my sample. Standard errors are clustered at the month-year-department level.

1.5.2 Results

Table 4: OLS Models Comparing Employed and Unemployed Returnees' Use of Networks

	(1)	(2)	(3)	(4)
Employed	0.26***	0.28***	0.28***	0.28***
	(0.02)	(0.02)	(0.02)	(0.02)
Age (years)		-0.01*	-0.01*	-0.01*
		(0.00)	(0.00)	(0.00)
Age^2		0.00**	0.00**	0.00**
		(0.00)	(0.00)	(0.00)
Female		0.01	0.03+	0.03+
		(0.02)	(0.02)	(0.02)
Married		-0.04	-0.01	-0.01
		(0.03)	(0.03)	(0.03)
Education				
No education			Ref	Ref
HS or less			-0.12***	-0.12***
			(0.04)	(0.04)
Tertiary or more			-0.38***	-0.38***
			(0.04)	(0.04)
Household				
Household Size				0.00
				(0.00)
Constant	0.66***	0.73***	0.87***	0.87***
	(0.06)	(0.09)	(0.10)	(0.10)
Month f.e.	YES	YES	YES	YES
Department f.e.	YES	YES	YES	YES
Observations	2580	2580	2580	2580

Notes: Coefficients from linear probability models. Sample is restricted to return migrants from Venezuela. Standard errors in parentheses. Employed indicates individual is employed at time of survey, unemployed and searching for a job is base category. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household over age of 12 [verify exact age]. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

In Table 4, I present the results from this regression. In Model (4), with a full set of controls, I see employed return migrants are 28% more likely to have used networks to find their most recent job, compared to the job search method of unemployed return migrants searching during the same month. This indicates that unemployed searchers are primarily using something *other* than networks to search, but that those who found a job, found it through networks. Indeed, a crosstab of the data shows that unemployed return migrants are more likely to bring or send their resume directly to employers than to use networks, indicating their preference for the former method.

This lends strong evidence in support of H2, that return migrants experience barriers to finding jobs through non-network channels, and thus are pushed towards using networks. While return migrants appear to have a preference for applying directly to companies, they are less likely to find a job in this way. This could be because their international experience is discounted, as is the case of Mexican migrants returning from the US (Lindstrom, 2013). Further, the fact that they are untrained in current labor markets can mean their skills are not aligned to local employer needs (Cobo et al., 2010; Lindstrom, 2013). It could also be that their status as a ”failed” migrant stigmatizes them to employers, making it harder to find a job using formal channels, consistent with other work about deportees around the world (Brotherton & Barrios, 2011; Dingeman, 2018; T. M. Golash-Boza, 2015; Schuster & Majidi, 2015). This points to the use of networks to reintegrate as a ”last” resort for return migrants (Cassarino, 2004).

Further, it does not appear that household size is an important mechanism to explain return migrants being more likely to use networks to find work. While the coefficient on household size is positive and significant, it does not affect the estimates when included as a control. However, it is possible that being a returnee gives return migrants a built-in network of other returnees which could provide them with employment, as is the case among deportees from the USA (Anderson, 2015; Brotherton & Barrios, 2011; T. M. Golash-Boza, 2015). This would not rule out the ”last resort” hypothesis, but explain how return migrants may activate their networks during this last resort search. It is possible that the household covariate does not adequately capture the extended family networks available to the returnee. It could be that returnees have larger networks of family support beyond the household, and that they access these ties to find work upon return. Future work with more granular network data is needed to fully explore this hypothesis. Broadly, these findings do not support the idea that return migrants cut ties with their connections when they leave, or at least not completely.

1.6 Returnees that Use Networks Find Lower Quality Jobs

1.6.1 Methods

I next test Hypothesis 3, jobs that return migrants find using networks are likely to be lower quality than those found using other means. I estimate the following OLS equation, for the first entry in Table 5, for job type. The sample here is restricted to return migrants from Venezuela to Colombia, who returned in either the past year or 5 years.

$$Y_{ij} = \alpha + \beta_1 net_{ij} + \beta_2 \mathbf{X}_{ij} + \delta_i + \gamma_j + E_{ij} \qquad (4)$$

Where Y is a binary outcome that takes a 1 if return migrant is a salaried worker, 0 otherwise indexed by month job was found i and Colombian department j. α is a constant. *net* is an independent variable that takes on a 1 if return migrant used a network connection to find their job, 0 otherwise. **X** is a vector of demographic covariates which are: gender, age, marital status and education, and household size. I also include a control for reason for return, which can take one of three values: 0 if reason is "exogenous", 1 if reason is work, and 2 for all other reasons. δ is a fixed effect for month-year job was found, and γ is a fixed effect for one of 24 surveyed departments. I exclude months and years before January 2012, because this is before return migrants in my sample had returned to Colombia. Standard errors are clustered at the month-year-department level. I estimate this equation for the 12 dependent variables in the table below.

1.6.2 Results

Table 5: OLS Models of Job Outcomes Among Returnees Who Used Networks Versus Returnees Who Did Not

	Coefficients (controls not shown)
Job Type	
Salaried Worker	-0.2***
	(0.04)
Domestic Worker	0.15***
	(0.04)
Day laborer	0.05**
	(0.02)
Industry	
Raw Materials	0.07**
	(0.03)
Manufacturing	-0.01
	(0.06)
Retail	-0.03
	(0.05)
Commercial Services	-0.11
	(0.07)
Health and Education	-0.07+
	(0.04)
Domestic Services	0.14***
	(0.04)
International	No obs
Job Quality	
Income (in 100,000s pesos)	-0.93
	(0.68)
Quality Index	-1.71***
	(0.35)
N	522

Notes: Coefficients from linear probability models. Sample is restricted to return migrants from Venezuela. Standard errors in parentheses. Employed indicates individual is employed at time of survey, unemployed and searching for a job is base category. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

Table 5 shows results where each coefficient shows the relationship between using networks and a different outcome (job type, job industry or job quality) variable. Only the β_1 coefficients on net_{ij} are shown for each of the 12 regression results in this table. Each coefficient is from a different model with all controls - coefficients for controls are not shown. I see that using networks is associated with a decrease in probability of finding job as a salaried worker, but increased probability of being a domestic worker or day laborer, which are typically lower status occupations. Looking at the *Industry* rows, I see that returnee's use of networks is positively associated with finding work in raw material extraction ($p<0.01$) and domestic services ($p<0.001$), and negatively associated with work in health and education ($p<0.1$). Again, using networks appears to be linked to industries with lower status occupations. Further, because health and education industries in Colombia are public sector jobs, this indicates that formal or non-network channels are more likely to provide access to this desirable work. These findings align with research on networks that shows that using networks may not result in high quality work, particularly for lower status or racial minority individuals (McDonald & Day, 2010; Pedulla & Pager, 2019; Smith, 2005).

The final rows of Table 5 show the relationship between using networks and two measures of job quality: income and the Quality Index (see Data and Measures). We see that return migrants that found their jobs through networks did not have a statistically significantly lower salary, however, their jobs are on average *lower* quality. In fact, jobs found through networks are, on average, 1.7 points lower on the index, or 0.72 of a standard deviation – a sizable association.

These findings are relatively unsurprising in the context of ”last resort” use of their networks. I show above that returnees appear to prefer *not* to use networks in their search. This could be due to an awareness that jobs found using networks are likely to be lower quality, offering fewer pecuniary and non-pecuniary benefits. This echoes findings that using contacts to find work does not yield higher salaries (Elliott, 2000; Green et al., 1999) including specifically for migrants (Pfeffer & Parra, 2009).

While I cannot speak specifically to occupational mobility because I do not have data pre-return, these findings lend support to overall downward occupational mobility of return migrants (Lindstrom, 2013). While many find mixed results on whether returnees are upwardly or downwardly mobile (Carletto & Kilic, 2011; Cobo et al., 2010; Mezger Kveder & Flahaux, 2013), none consider job search strategy upon return as a potential mechanism. However, as I show, use of networks is associated with lower quality jobs, even after controlling for migrant, job and industry characteristics. Further research will need to examine *why* return migrants who use networks have worse occupational outcomes than those who don’t. There could be unobservable characteristics that are correlated with both job outcomes and job search strategy. For example, being a good writer and putting together a strong direct application may signal ability to enter white collar employment, which is typically higher paid with more benefits. Others suggest that using networks leads to higher likelihood of finding work, but only for the informal sector, indicating that those with preference to find a job quickly in this sector may use their networks (Diaz, 2012).

1.7 Discussion and Conclusions

This paper explored the job search strategy and occupational quality of return migrants and forced return migrants. My general focus was on whether return migrants have connections available to help them upon return, and whether they draw on these to find a job. The context of this paper is the mass return event of Colombian migrants from Venezuela since the 2010s. First, I demonstrate that return migrants, particularly unprepared ones, are more likely to use their networks to find jobs than never migrants. This result holds for those who returned in the last year, and for those who returned due to threats to their life, well-being or natural disasters. Difference-in-differences estimates that exploit deportations and forced returns from Venezuela in 2015 show similar results.

Second, I examine whether this use of networks among returnees was due to preferences, access to larger networks through larger households, or as a last resort, as proposed by Cassarino (2004). I find correlational evidence that return migrants use networks as a last resort, and their preference would be to apply directly to employers. This may be due to their skills being discounted upon return (Lindstrom, 2013), or employers discriminating against them as "failed" migrants (T. M. Golash-Boza, 2015). It also does not seem to be the case that return migrants have larger households which may provide them with more ties to use in a search. However, it remains unclear whether they may have more networks available to them outside the household, either in the form of extended family support (Schuster & Majidi, 2015), or in the form of networks of returnees. For example, there are reports of young deportees relying on networks of earlier returnees to get work in call centers or tourism (Anderson, 2015; Brotherton & Barrios, 2011; T. M. Golash-Boza, 2015) where they can use their foreign language skills. Further research will need to examine the mechanisms through which return migrants access networks that offer job support.

Third, I find that the use of networks results in lower quality, lower status work among returnees, compared to those that do not use networks. Notably, return migrants in my sample are more likely to be domestic workers or day laborers, and less likely to be salaried workers. They work in industries with lower prestige (e.g., domestic services) and have lower job quality on a scale made up of 9 different quality measures. These results echo findings from Colombia that those who use networks to obtain lower paid jobs (Diaz, 2012; Nicodemo & García, 2015).

One of the main limitations of this paper is the lack of panel data and the potential measurement error inherent in estimating exactly when migrants returned. While I implemented multiple strategies to understand returnee's job search and job history, there is still a risk that I am capturing their second job upon return. If returnees lose their networks when they move abroad, then it is possible they do not have them immediately available to them upon return and have only built up these networks by the time of their second job search. On the other hand, if returnees are seen as 'failed' or have a long job history mis-aligned with local employer needs, then they will be forced to use networks as a last resort regardless of whether they are searching for their first or second job upon return. The latter is the more likely scenario, evidenced by the fact that returnees are more likely to try applying directly to employers, but ultimately land jobs using networks. This suggests that it is not a matter of not having networks available, but instead that return migrants experience barriers to finding work using other means. Another limitation is that I do not have more granular network data. For example, whether a returnee found their job through a family member, friend, or former colleague is impossible to disentangle in my data and could lead to interesting interpretations of results. Studies of returnees to Afghanistan show that family may turn their backs on the returnee, especially when their return is stigmatized as in the case of deportation (Schuster & Majidi, 2015). In this case, whether the job help comes from friends or family can provide important context clues to uncovering the full story of returnee reinsertion.

Future research will need to combine mixed methods, panel, and/or network data from a similar setting to understand the experiences of returnees seeking work in a largely informal economy during a time of upheaval. However, this paper presents a springboard from which to answer some more detailed questions about mechanisms and employment outcomes through a job search lens.

Given the existing debate about whether immigrants maintain their networks when they move abroad, it is important to understand whether return migrants would have networks available to them when they return to their home country. This paper finds that, indeed, returnees use their social networks to find a job upon return from another country. I build on research suggesting that immigrants who make an unprepared return are forced to rely on their networks, because they do not have time or resources to integrate by other means (Cassarino, 2004). Policy programs that support formal returnee incorporation may be better aligned to returnee goals, who appear to use networks as a last resort, and not as a preference.

2. Identifying Immigrant Typologies Through Networks

This Chapter examines the assimilation patterns of Chinese immigrants in the Raleigh-Durham Area and is a joint work with Giovanna Merli and Ted Mouw. I led the analysis and writing of this chapter, the data collection was led by Giovanna Merli and Ted Mouw.

2.1 Introduction

How do social network mechanisms underpin existing accounts of assimilation? Early works on immigrant assimilation conceptualized assimilation as a one-sided process of immigrants' full incorporation into the host country (Glazer & Moynihan, 1963; Gordon, 1964). By contrast, later works have sought to emphasize the role of both immigrants and their local hosts in the former's process of incorporation (R. Alba & Nee, 1997; Portes & Rumbaut, 2001; Zhou, 1997). These theories stress the fact that immigrants with different characteristics and migration histories may have different experiences with assimilation to the host culture. For example, segmented assimilation posits that immigrants welcomed into enclaves that provide them with resources and opportunities can be upwardly mobile, unlike those without this form of support (Portes & Zhou, 1993). Scholars in the transnationalism tradition highlight that frequency of contact and nature of international ties can either aid, slow down or alter the nature of immigrants' social incorporation (Portes et al., 1999). Social networks and social capital theories suggest that immigrants draw on their networks to access information and support as they arrive in a new country, and these ties can constrain or facilitate assimilation (Lancee, 2012; Portes & Shafer, 2007; Ryan, 2011; Ryan et al., 2008; Wilson & Portes, 1980).

Yet many of the empirical observations consistent with these arguments do not cleanly translate into the context of newer immigrant groups, many of whom are settling directly into suburban areas (Alba et al. 1999; J. Lee and Kye 2016; National Academy of Sciences Engineering and Medicine 2015). For one, the rise of a transnational class has allowed for immigrants connected to their home country to maintain their high status abroad (Waldinger, 2015a). Simultaneously, with the rise of social media and smart phones, maintaining both local and international connections is increasingly easy and cheap, meaning that leading a connected life is possible for immigrants of all backgrounds and origin.

The purpose of this paper is to explore how these arguments interact to explain assimilation. To do so, we draw on a unique data set and machine learning methods to understand the assimilation of a group of first-generation immigrants in a new immigrant destination in the U.S. South: Chinese immigrants in the Raleigh-Durham Area (RDU) of North Carolina. This region is home to three major universities, large university health systems as well as many IT and pharmaceutical companies, attracting a large population of immigrants from China and India (Tippett, 2018) who are settling across largely suburban areas (J. Lee & Kye, 2016; National Academy of Sciences

Engineering and Medicine., 2015). We use personal network surveys of first generation Chinese migrants collected for the *Chinese in the Raleigh Durham Area Study* (ChIRDU) (Merli et al., 2022). The surveys collect information on respondents' ties to other Chinese immigrants in the local area, local non-Chinese individuals, and Chinese individuals living in China or elsewhere outside the U.S. These network surveys are focused on friend and acquaintance networks. We then use clustering algorithms to categorize respondents into groups. Specifically, we employ finite Gaussian mixture models to identify four immigrant typologies in our sample: *Chinese Friendship Networks*, *Socially Embedded*, *Undecided Newcomers*, and *Economically Integrated*. Each of these groups is differentiated by their personal networks as well as demographic characteristics. We find that these clusters are associated with some key assimilation indicators: Satisfaction with life in the USA, Partly American or Chinese identification, employment, and income, among others.

2.2 Theoretical Background

2.2.3 Assimilation Theories

One of the earliest conceptions of assimilation, "structural" assimilation, explains this process as one where minorities integrate into institutions of the white majority (Gordon, 1964). The first step in this model is *acculturation* to middle-class white America, where cultural pattens of the majority are adopted by the minority group, a process which eventually facilitates assimilation (Gordon, 1964). This and other early assimilation frameworks (Gans, 1992; Glazer & Moynihan, 1963) have since been repudiated for presenting a linear view of the immigration process; one where immigrants unilaterally adapt to the majority group in the host country over multiple generations. Alba and Nee nod to structural assimilation theory, noting its weaknesses, and expand on it through the development of a new theory of assimilation (R. D. Alba & Nee, 2003; R. Alba & Nee, 1997). They conceive assimilation broadly as the disappearance of ethnic and cultural distinctions, though not necessarily of the erasure of differences in ethnicity. Notably, this theory emphasizes changes in culture and attitudes of the majority group in the host country, such that eventually ethnicity is no longer a barrier to economic or educational achievement (R. D. Alba & Nee, 2003). Alba and Nee posit that assimilation means ethnic and racial differences are dampened through changes to both the immigrant culture and the majority group, noting that American culture is not the homogenous middle-class Anglo-Saxon conception that Gordon put forth (R. D. Alba & Nee, 2003).

As an alternative to classical assimilation theories, segmented assimilation theory emerged in the early 1990s, in part to explain how immigrants from newer destinations in Latin America and Asia have assimilated to different "segments" of society (Portes and Zhou 1993). This theory proposes that different circumstances will prompt immigrants to take one of three paths towards assimilation. The first follows classical structural assimilation and involves acculturation to the white, American, middle-class society; the second involves assimilation to the urban underclass, “downward assimilation”, resulting in the inability to overcome poverty; the third proposes economic advancement while maintaining home-culture and immigrant solidarity (Portes and Zhou 1993). Part of this approach to understanding immigration has underscored ethnic enclaves as central features of immigrant life, which can either lead to a model for business and stability as in the case of the Cuban enclave in Miami, or, when smaller and less organized, can lead to discrimination and marginalization as is the case for Jamaican immigrants in Miami (Portes & Zhou, 1993). Networks also play a central role in segmented assimilation theory. The authors point to the importance of connections to the co-ethnic community when immigrants are seeking resources. In turn, resources flow through these networks to benefit newcomers (Portes & Zhou, 1993). However, while segmented assimilation conceived of enclaves broadly as sources of social support and access to resources, authors did not collect personal network data to test this assimilation hypothesis, meaning that some intricacies of how assimilation operates through networks remains unexplored.

It is known that immigration is an inherently networked process; migrants will go where they already have established connections and, in their place of destination, they tend to be connected to individuals from their region of origin (Boyd, 1989; Durand & Massey, 1992; Massey, 2004). Much of this work focuses on the composition of immigrant ties to understand their outcomes. For instance, bonding ties (ties connecting the immigrant to the majority group) are more fruitful for social and labor market incorporation than bridging ties (ties among co-ethnic immigrants) (Lancee, 2012). Other work finds that co-ethnic ties can be fundamental to acquiring basic resources or work upon arrival, but that relying exclusively on these ties overtime can negatively constrain migrants (Ryan et al., 2008). Indeed, a longitudinal network study following immigrants since their arrival at destination found that those who have been at destination for shorter duration are more likely to hold on to local native-born contacts, whereas those who have longer stays hold on to their foreign-born ties (Lubbers et al., 2010).

As a response to theories that present assimilation as a process occurring only at destination, transnational theories propose to incorporate immigrants' ties to individuals in both origin and host countries (Dahinden, 2017; Portes et al., 1999, 2002; Schiller et al., 1992; Vertovec, 1999; Waldinger, 2015a; Waldinger & Fitzgerald, 2004). Much of this work has sought to understand the process of economic and labor market assimilation of immigrants through their transnational connections on which they rely for resources, stemming from an overall increase in cross-border activities thanks to globalization and the digital economy (Waldinger, 2015a). As the cost of maintaining transnational ties decreases, immigrant economic success relies increasingly on cross-national networks (Portes et al., 1999). Over the past decade, researchers have begun to incorporate social networks analysis into the study of transnationalism, in part to understand how interaction and personal connections are inherent to the migration process (Bilecen et al., 2018; Lubbers et al., 2020). For example, the collection of cross-border ties has allowed one to better understand the importance of international connections for the immigration process (Mouw et al., 2014). While some transnational connections are replaced by local ones as time since migration increases, networks between origin and destination remain, which can explain information flows (Verdery et al., 2018b). Indeed, transnational connections can be a source of support for immigrants in their incorporation process (Bilecen & Cardona, 2018).

The terms "assimilation" and "integration" have sometimes been used interchangeably; however, they have different origins which has altered their meanings overtime. Assimilation, typically used in migration literature from the Americas, is distinguished by the existence of a concept of a 'mainstream', though, as discussed above, the mainstream need not be static. Integration, a term largely used in the literature from Europe, focuses more on policy and measures, such as educational and labor outcomes (Schneider & Crul, 2010). This paper focuses on assimilation theory, due partially to its geographic focus and its application of networks, which has been central to recent assimilation frameworks. However, when addressing labor market and income indicators in particular, we will focus on "integration", the term most closely aligned with this framework. We will follow Alba and Nee (2003) and define acculturation as the cultural equivalent of assimilation- the uptake of cultural characteristics from the majority group or the adoption of minority culture by the majority group, attenuating the cultural differences between the two.

This paper seeks to combine information on social networks both at destination and transnationally, to better understand the assimilation process for Chinese immigrants in the Raleigh-Durham area. It is worth mentioning that a large portion of the literature on segmented assimilation has largely focused on second generation outcomes (Haller et al., 2011; Portes & Rumbaut, 2001, 2005; Portes & Zhou, 1993; Rumbaut, 2008). While the data we examine here were collected among foreign-born Chinese, understanding assimilation patterns of the first-generation immigrants can provide important insights for their own assimilation process, and that of their children.

2.2.4 Identifying Immigrant Typologies

Existing work on immigrant typologies use immigrant characteristics to identify ideal types and understand heterogeneity in factors influencing migration (Drouhot & Garip, 2021; Garip, 2012, 2016), acculturation to the host society (Berry, 1997), and transnational living (Dahinden, 2009), with recent calls to bring this perspective to assimilation (Alba 2017). Because few scholars have been able to tackle social networks and assimilation simultaneously, mostly due to a lack of appropriate data, previous work on the assimilation of new immigrants has typically considered questions of immigrant incorporation separately from networks, in part because migrant networks are complex and transnational (Mouw et al., 2014; Verdery et al., 2018b).

Over the past 15 years, some work has addressed the importance of immigrant networks, and sought to use them as a base for developing typologies or "ideal-types". Lubbers, Molina, and McCarty (2007) analyzed personal networks of immigrants to Spain. Using a k-means clustering algorithm on nine variables related to structural network characteristics and composition of ego-centric networks, they find five distinct types of immigrants among the 280 respondents in their sample. Those who maintain a majority of their contacts in their country of origin are more likely to have a transnational ethnic identification, meaning their self-identity crosses borders (e.g., Latin American), which is the same self-identification as those with a mix of friends at destination who are either native-born Spaniards or immigrants from their home country. However, those with dense family networks, have stronger *ethnic* self-identification, associated with their home country (e.g. Dominican). Brandes and colleagues (2010) classify the personal networks of a combined sample of 504 immigrants in Spain and the USA. They use a method similar to blockmodeling which condenses information on node attributes and structure into a single measure. Next, they partition these ensembles and identify either four or eight clusters. In particular, the four cluster typologies they identify map onto Berry's acculturation framework (separation, integration, marginalization and assimilation) (Berry, 1997). Vacca et al. (2018) use the personal network structure of Moroccan, Senegalese and Gambian immigrants in Spain (N = 139), and of Sri Lankan immigrants in Italy (N = 102) to understand economic and assimilation indicators such as language use, home-country identification, as well as income to measure economic assimilation. They use k-medoid clustering analysis (PAM algorithm) and cluster on size and cohesion of native and origin co-national personal networks. This method provides much-needed nuance in network structure to understand assimilation. They find that acting as a broker between native and co-national individuals holds the highest likelihood for assimilation. These papers provide important insight into the classification of immigrants by their network structure, with a focus on collecting large number of ties for smaller sample sizes, among a variety of immigrant groups, mainly in Europe.

Given the variability in numbers of immigrant typologies identified in the existing literature (Brandes et al., 2010; Drouhot & Garip, 2021; Garip, 2012; Lubbers et al., 2007; Vacca, 2020), it is unclear how many distinct typologies there are among Chinese immigrants, the object of this study. We pose our first question:

Q1: How many types of Chinese immigrants do we identify using ego-centric network data?

2.2.5 Asian and Chinese Assimilation in the USA

Recent attention has been paid to the assimilation process of Asian immigrants to the US. Asian immigrants are now the fastest growing immigrant group, with 81% growth from 2009 to 2019 surpassing the growth in Hispanic immigrants at just 70% (Budiman & Ruiz, 2021). Chinese immigrants in particular make up nearly a quarter of all Asians in the U.S., China is now the second most common birthplace of immigrants in the US, after Mexico, and 62% of Chinese individuals in the US are foreign born (Batalova, 2021; Budiman, 2021).

Asian immigrants, Chinese in particular, have achieved high levels of socioeconomic success (Kasinitz et al., 2009; Lueck, 2018; Nee & Holbrow, 2013; Sakamoto et al., 2009; Zhou & Gonzales, 2019). This has been attributed by some to an increase in educational and occupational achievement (Greenman & Xie, 2008; Hsin & Xie, 2014), and selectivity of immigrants coming from China making them both more educated than non-migrants in China as well as whites in the USA (J. Lee & Zhou, 2017). In fact, being a first generation Chinese immigrant is associated with a higher likelihood of having a high school degree than being second or third generation (Greenman & Xie, 2008).

Others maintain that, despite economic and educational gains, Asian Americans continue to experience disadvantage due to racialization which constrains opportunities even for second generation immigrants (J. C. Lee & Kye, 2016; Sakamoto et al., 2009). Chavez (2021) finds that all Asian groups in their sample, including Chinese immigrants, are less likely to get job offers compared to other ethnicities, in part because they are perceived as a poor "cultural fit". There is evidence that both Asian Americans and foreign-born Asians (including Chinese men, specifically) hit a career ceiling when seeking management positions and experiencing wage discrimination vis-à-vis their white counterparts at higher levels of the corporate ladder (Gu, 2015; M. Kim & Mar, 2007; Takei et al., 2014; Takei & Sakamoto, 2008; Woo, 2000). Asian women have been shown to supervise fewer employees than white women on average, though this finding is directionally consistent but not statistically significant for first generation Chinese immigrants (C. Kim & Zhao, 2014).

Ethnic boundaries between Asian immigrants and other groups, however, may contribute to their success in the long term as they provide resources in the form of jobs and connections when immigrants first arrive (J. C. Lee & Kye, 2016; Wilson & Portes, 1980). Indeed, maintaining a strong ethnic identity can be crucial to the assimilation experience of the Chinese immigrant community (Kasinitz et al., 2009; Zhou, 2014). Zhou (2014) emphasizes the importance of "extensive networks of social support" (p 1182) as a key determinant of Chinese immigrant assimilation. Chinese professionals often reside in communities with other Chinese immigrants who have a lower SES background, and provide intra-ethnic support through the provision of information and resource (Kasinitz et al. 2009, p 362). In this paper, we observe in our data Chinese immigrants across the SES spectrum, making this a particularly useful population to study the links between social ties and assimilation outcomes (Kasinitz et al., 2009).

The portrayal of Asians as a monolithic group has contributed to the persistence of the Model Minority Myth, which paints Asians in the US with the same brush - as high-achieving and thus having overcome discrimination (Sakamoto et al., 2009), which has led to Asian stereotypes. Treating this group as homogenous is therefore both problematic and does little to advance our understandings of assimilation in theory and practice.

As a response to this, recent developments in the literature on Asians in the USA have emphasized that the treatment of Asians as a single category masks great heterogeneity in the experience of race, identifying five different classes, and how discrimination may operate differently within each of them (Drouhot & Garip, 2021). In particular, they find that categories differ on whether they identify strongly with their race, have received poor treatment, perceive a racially-linked fate and have experienced the model-minority stereotype (Drouhot & Garip, 2021).

Assimilation researchers have emphasized differences within the Asian category among different axes to explain or deconstruct educational and labor market achievements of this group including legal status (Nee & Holbrow, 2013); inter-ethnic friendship (Greenman & Xie, 2008); resources from countries of origin (J. Lee & Zhou, 2017) ; and support networks (Kasinitz et al., 2009).

We take the same approach in rejecting homogeneity among categories and seek to understand how differences in immigrant characteristics combine to affect immigrant outcomes by developing Chinese immigrant typologies.

There is a budding literature on intra-group heterogeneity among Chinese immigrants in particular. In the UK, for example, labor market outcomes (wage and employment) vary depending on whether immigrants are from mainland China, Taiwanese-born, Malaysian-born Chinese, from Hong Kong, or UK-born. Studying this heterogeneity has helped unmask the importance of local networks and immigrant cohort effects (Mok & Platt, 2020). Wealth levels are higher on average for Mainland Chinese immigrants than Taiwanese or Hong Kong immigrants in the US, and tenure at destination plays an important role in wealth accumulation, underscoring a different dimension of heterogeneity (Keister et al., 2016). Qualitative evidence from Canada shows that Chinese immigrants are divided along linguistic lines (Mandarin and Cantonese) and this shapes access to networks and opportunities (Yan et al., 2019).

This body of work underscores the importance of understanding subethnic differences in immigrant experience. While each of these studies focused on heterogeneity based on origin, language, or cohort, our paper recognizes that networks shape opportunities and is thus an important source of heterogeneity and heterogeneity is multi-dimensional and cannot be adequately captured looking at one or two observable characteristics, as outlined in Drouhot and Garip (2021). Given that both network and demographic characteristics (like origin, income, and gender) have been shown to shape immigrant experience and assimilation, we pose our second question:

Q2: What does each Chinese immigrant typology look like in terms of network and demographic characteristics?

As explained above, segmented assimilation theory, has shown to be a useful lens to examine the process of Chinese immigrants' incorporation in the USA (Zhou, 2014), as is assimilation theory which has been applied to Chinese economic assimilation (R. Alba & Nee, 1997), and more recently racialized assimilation frameworks have been proposed to understand Asian immigrant experience (J. C. Lee & Kye, 2016). We build on works on immigrant typologies, and Asian immigrant typologies in particular, putting into conversation personal network information and assimilation frameworks, (Bilecen et al., 2018; Drouhot & Garip, 2021; Lubbers et al., 2007; Vacca et al., 2018), and thus pose question 3:

Q3: How are the identified immigrant typologies related to existing assimilation frameworks?

and

Q4: Do we see any correlation between clusters and indicators of assimilation?

In answering the four questions we contribute to the existing literature in three key ways. First, we examine an under-studied immigrant population group, Chinese immigrants, in a new immigrant destination (Flippen and Kim 2015; Sakamoto, Kim, and Takei 2013). Here, we build on work that shows that Chinese immigrants who live outside of traditional gateways in the US have a higher socioeconomic status on average than those in more traditional areas (Flippen & Kim, 2015). Understanding how network factors may correlate with SES in these areas is important to understanding migrant incorporation for this unique group.

Second, we provide additional evidence of immigrant incorporation thanks to a rich survey administered to 513 participants. For example, in addition to three network rosters enumerating tie type and frequency of contact, we have a unique battery of questions on respondents' perspectives on life in the USA, a large number of employment-related questions which measure variables relevant to the understanding of assimilation including what proportion of workplace employees are Chinese and how many hours a week are worked.

Third, we generate clusters by implementing a model-based clustering method which improves on k-means clustering by being non-prescriptive about the number of clusters in the data. This method allows for the incorporation of continuous variables, which allows one to use "proportion of contacts who are co-workers" as a continuous measure instead of an arbitrary dichotomy, which can reduce precision. Clustering methods are similar to Latent Profile Analysis (LPA) or Latent Class Analysis for categorical variables which has been used to define immigrant typologies elsewhere (Drouhot and Garip 2021), in that they both partition the sample into different groups and are both considered unsupervised classification models in machine learning. Model Based Clustering and Latent Profile Analysis are both *model-based* clustering methods, meaning they both assume there are existing sub-populations in the data that can be modeled using Finite Mixture Models. While similar, model-based clustering executed in the *mclust* package (Scrucca et al. 2016) is slightly more flexible in that it allows us to find the optimal number of clusters and the best model fit by iterating through multiple models, instead of just one.

The following sections detail the data and methods, the clustering results, the assimilation results, followed by the discussion and conclusion.

2.3 Data and Methods

2.3.1 Data

We rely on a sample of 513 Chinese foreign-born individuals age 18+ residing in the Raleigh-Durham area of North Carolina, collected for the Chinese in the Raleigh Durham Area (ChIRDU) Study (Merli et al. 2022). This sample was recruited using Network Sampling with Memory (NSM) (Merli et al., 2016; Mouw & Verdery, 2012). NSM is a link-tracing sampling design which capitalizes on the network structure of the target population to identify and interview multiple waves of respondents and uses post-recruitment weighting of cases to correct biases towards sampling popular individuals. As part of the study, participants were asked to nominate six friends on a roster who were also Chinese-born and lived in the RDU Area using minimally identifying information. These rosters were then used in the sampling process as the algorithm would sample from this list to select the next respondents to be contacted to participate. This allows us to generate a sample of our target population while using the minimally identifying information to map the underlying network of contacts.

Clustering algorithms, the main method employed in this study, cannot operate with missing data. The nature of the variables makes them difficult to model and we thus choose to keep only observations where the key clustering variables are available. The final N is 413. As a robustness check, we perform multiple imputation on the network variables used to cluster. The clusters look largely similar to the clusters we find in our main results, with a consistent optimal number of clusters and main cluster characteristics. See Appendix B.

As part of this study, we collected three ego-centric or personal network rosters, where only the first (Roster A) was used in the sampling procedure. Roster A collected information on up to 6 contacts residing in the Raleigh-Durham Area who are born in mainland China, Hong Kong or Taiwan. Roster B collected information on up to three local non-Chinese-born contacts, and Roster C collected information on up to 3 Chinese born contacts outside of the Raleigh-Durham Area. In order to maximise the number of nominations, we administered a name generator to elicit names (see wording further in this section), followed by questions about key attributes and relationship characteristics to each tie. Respondents were then asked for contact information. Descriptive statistics from these Rosters are in Table 6. All values are shown as a proportion of nominations. For example, if an individual nominated three co-workers out of six possible nominations, they would have 0.5 of their nominations in the co-worker category. The entry for Roster A Co-worker in the table represent the average proportion of rosters made up of co-workers in the sample.

For Roster A, we presented the following questions: *Please provide the Chinese first name, English first name (if they have one), and the first initial of the last name 6 people you know who were born in China, Taiwan or Hong Kong, who are 18 or older and who reside in the Raleigh/Durham/Chapel Hill area. These are people whose name you know and who know yours and with whom you might stop and talk at least for a moment if you ran into them on the street.* From Table 6, we see the majority of connections nominated in Roster A are friends (72%), with smaller portions attributed to the co-worker (10%), neighbor (5%), or relative (12%) categories. The results for frequency of contact were more mixed, with most speaking to their contacts weekly (43%), followed by monthly, daily and once or twice a year.

For Roster B, we used the name-generator: *Please provide the first name (or initial) for 3 people you know who were NOT born in China, Taiwan, or Hong Kong, who are 18 or older and reside in the Raleigh-Durham-Chapel Hill area. These could include your co-workers, friends or even people whom you know only a little who were born in the U.S. or in places OTHER than China, Taiwan, or Hong Kong.* In Table 6, we note that the most frequent response is friend, that is on average 39% of the three Roster B nominations per respondent. The second largest category is co-workers, followed by neighbor then other. In terms of ethnicity, on average 2 out of 3 nominations are white, this is followed by other Asian (16%), Black (8%) , then Hispanic and Chinese American. The contact with these individuals is relatively distributed: daily is the most likely frequency (35%), followed by weekly (32%), daily (19%) with once or twice a year representing only 13% of contacts.

For Roster C, we asked: *Now please provide the first name (or initials) for 3 people you know who were born in China, Taiwan, or Hong Kong, who are 18 or older and who reside OUTSIDE of the Raleigh-Durham Area.* We find that the majority maintain contact with friends (55%) and most of these ties reside in China (88%). This contact is relatively infrequent with two thirds having contact once a year or less. In addition to personal network rosters, the ChIRDU study collected rich individual-level survey data from 513 Chinese immigrants, including the 413 respondents in our sample.

Individual questionnaires included information on demographic and socioeconomic characteristics, employment, and assimilation indicators seen in Table 7. Table 7 shows the rich detail of the ChIRDU survey. Importantly, we are able to separately examine employment characteristics as well as acculturation and feelings of Life in the USA, which will help us understand assimilation among the different groups in our sample.

Table 6: Roster Descriptive Statistics (in Proportion of Nominations)

		mean	sd	min	max
Roster A	*Nature of Connection (n missing=70)*				
	Co-worker	0.10	0.22	0	1
	Friend	0.72	0.32	0	1
	Neighbor	0.05	0.14	0	1
	Relative	0.12	0.22	0	1
	Frequency of Contact (n missing=70)				
	Daily	0.22	0.29	0	1
	Weekly	0.43	0.33	0	1
	Monthly	0.26	0.29	0	1
	Yearly	0.08	0.18	0	1
Roster B	*Nature of Connection (n missing=73)*				
	Co-worker	0.37	0.4	0	1
	Friend	0.39	0.39	0	1
	Neighbor	0.13	0.24	0	1
	Other	0.1	0.23	0	1
	Ethnicity/Origin (n missing=73)				
	Chinese American	0.05	0.16	0	1
	Asian	0.16	0.24	0	1
	Black	0.08	0.17	0	0.67
	Hispanic	0.04	0.15	0	1
	White	0.67	0.32	0	1
	Frequency of Contact (n missing=73)				
	Daily	0.35	0.38	0	1
	Weekly	0.32	0.34	0	1
	Monthly	0.19	0.26	0	1
	Yearly	0.13	0.27	0	1
Roster C	*Nature of Connection (n missing=72)*				

Co-worker	0.03	0.13	0	1
Friend	0.55	0.36	0	1
Relative	0.37	0.36	0	1
Other	0.04	0.16	0	1
Contact's Geographic Location (n missing=72)				
China	0.88	0.25	0	1
Asia (not China)	0.02	0.09	0	1
North America	0.01	0.07	0	1
Europe	0.03	0.12	0	1
Oceania	0.02	0.09	0	0.67
Frequency of Contact (n missing=72)				
Daily	0.07	0.17	0	1
Weekly	0.33	0.35	0	1
Monthly	0.33	0.35	0	1
Yearly	0.26	0.36	0	1
N	413			

Notes: Values indicate proportion of roster. Rounded to the nearest 0.0. Because of different number of missing values in each category, may not add up to 1.

In our sample of immigrants age 18+, the average age of respondents is 43, 65% are female, 85% are married and have been in the USA for an average of 13 years. The majority (91%) are from Mainland China, 1% are from Hong Kong and 8% are from Taiwan. Our sample is highly educated. 83% have a college degree or more than a college degree, while only 17% have some college or less. In addition, 16% are students or postdocs. In terms of employment and income indicators, 72% of the entire sample has ever worked in the US, while 28% of working individuals used networks to find their job. Only 17% of the sample is paid hourly, which is an indication of the relatively high SES of this group. Indeed, the mean annual income is $72,000, though there are a lot of missing data for this variable.

Life in the USA indicators allow us to understand respondents' broad attitudes towards living in the USA and Americans in general. 55% of respondents indicate they like American culture while only 38% would like to completely adapt to life in the USA, and 39% identify partly or fully as American.

Table 7: Descriptive Statistics for Demographic Characteristics and Dependent Variables (Proportions and Means With SD in Brackets)

	mean	sd	min	max	N
Demographic Characteristics					
Age (years)	43.16	10.86	18.39	76.88	412
Female	0.65	0.48	0	1	413
Married	0.85	0.36	0	1	413
Time in US (years)	13.07	9.01	0.25	40	412
Origin					
From Mainland China	0.91	0.29	0	1	413
From Hong Kong	0.01	0.1	0	1	413
From Taiwan	0.08	0.28	0	1	413
Education					
High School or less	0.09	0.29	0	1	413
Some College	0.08	0.28	0	1	413
College	0.22	0.41	0	1	413
More than College	0.61	0.49	0	1	413
Is a Student or Postdoc	0.16	0.37	0	1	413
Other Characteristics					
Speaks English Very Well	0.21	0.41	0	1	412
Citizen or Green Card holder	0.76	0.43	0	1	413
Has a child over 16	0.41	0.49	0	1	195
Belongs to a church	0.42	0.49	0	1	413
Owns Property in China	0.22	0.42	0	1	410
Employment and Income Indicators					
Has worked in the USA	0.72	0.45	0	1	413
Owns a Business in USA	0.22	0.42	0	1	407
Used networks to find job	0.28	0.45	1	2	297

% of colleagues Chinese	24.66	32.35	0	100	268
Is paid hourly	0.17	0.38	0	1	287
Income (000s)	72.7	56.1	0	450	276
Weekly Hours	37.98	11.41	2	80	295
Life in the USA Indicators (Proportion that Agree)					
Like American Culture	0.55	0.5	0	1	413
I would you like to completely adapt to the USA	0.38	0.48	0	1	413
I Identify fully or partly as American	0.39	0.49	0	1	409
Scale of Satisfaction with Life in the USA					
Item 1 - Non-whites have as many opportunities to get ahead economically as whites in the U.S.	0.35	0.48	0	1	412
Item 2 - There is no better country to live in than the United States	0.20	0.4	0	1	407
Item 3 - The American way of life weakens the family	0.27	0.45	0	1	410
Item 4 - There is much conflict between different racial and ethnic groups in the U.S.	0.54	0.5	0	1	408
Item 5 - Americans generally feel superior to foreigners	0.65	0.48	0	1	410
Item 6 – There is racial discrimination in opportunities in the USA	0.68	0.47	0	1	408
Life in the USA Scale (Sum of Items 1-6)	2.41	1.43	0	6	394

Notes: Descriptive statistics among 413 surveyed Chinese immigrants in the Raleigh-Durham Area (RDU). Means are unweighted proportions, unless indicated otherwise. Life in the USA scale is calculated by summing Item 1, Item 2, Reverse code of Item 3, Reverse code of Item 4, Reverse code of Item 5, and the Reverse code of Item 6.

2.3.2 Methods

This paper follows previous work on network-based immigrant typologies (Brandes et al., 2010; Vacca et al., 2018) and uses cluster analysis, a method often applied in unsupervised machine learning that identifies groups of similar observations (Drouhot & Garip, 2021; Garip, 2012, 2016). Determining how multiple variables interact to affect outcomes can be costly both in terms of computational power and time through methods like regression (Drouhot & Garip, 2021; Garip, 2012). Previous works applied k-means algorithms which serve to find the lowest distance between points, based on a pre-specified distance metric (Garip, 2012).

One of the main drawbacks of k-means algorithms is that the number of clusters must be pre-specified. For our purposes, in seeking to understand how many groups emerge from the data, it is not practical to specify this number before clustering. While there are various optimizers that can identify the most likely number of clusters, each will yield different results at each time, making it difficult to determine the preferred optimal number. Furthermore, changing the initialization of the k-means algorithm can change the results due to a completely stochastic process, again making the results hard to interpret or spurious.

Model-based clustering methods have been proposed as a solution to some of the issues with k-means clustering algorithms mentioned here. These methods estimate the optimal number of clusters (without pre-specification) and probabilistically assign observations to each group. Here, we implement finite Gaussian mixture models using the **mclust** package in R (Scrucca et al., 2016). We estimate parameters for the following model:

$$f(x_i; \psi) = \sum_{k=1}^{G} \pi_k f_k(x_i; \theta_k)$$

Where there are G mixture components, ψ include the G parameters of the model [π_1, π_{G-1}] and [θ_1, θ_G] and π_k are the weights for the kth component where $f_k(x_i;\theta_k)$ is the component density for observation x_i. We then used the following procedure to determine the optimal numbers of clusters and group our observations.

Step 1: Feature Selection

Variable selection, or feature selection, is typically the first step in implementing any clustering algorithm. We begin with the 34 Roster A, B, and C variables presented in Table 6. The clustering then will occur over a subset of the variables that explain the largest proportion of the variance. Selection of key variables removes redundancy from the model-based clustering. There are dozens of ways to perform feature selection, but one of the most straightforward is a Principal Components Analysis (PCA) performed using a Singular Values Decomposition. PCA allows us to retain the network variables that explain the highest variation, ensuring that we are reducing redundancy while maximizing variation. However, it is possible that the variables that meet this condition are not theoretically or substantively meaningful. As an additional check, we perform a researcher-based variable selection process (See Appendix B) where we select eight roster variables based on knowledge of the sample and existing literature. We find the same number of clusters. The number of observations in each cluster changes which leads to some variation in cluster composition though we see the same broad patterns among network and demographic/migration history characteristics.

The PCA here is implemented using the **prcomp** package in R. First, we scale the variables. We then take the first component of the PCA which is the component that explains the highest proportion of the variance. Next, we look at the variables with the highest loadings (in absolute value) from the first component.

Table 8: Variable Loadings From First Principal Component

Roster B Cowork	0.548	Roster B Yearly	0.091	Roster B Other	0.020
Roster B Friend	0.485	Roster C Weekly	0.090	Roster C Other	0.016
Roster B Daily	0.452	Roster A Weekly	0.090	Roster B Black	0.016
Roster B Weekly	0.206	Roster A Monthly	0.076	Roster C China	0.012
Roster A Friend	0.192	Roster A Relative	0.051	Roster B Hispanic	0.009
Roster C Friend	0.170	Roster B White	0.044	Roster A Neighbr	0.006
Roster A Daily	0.169	Roster C Once a year	0.042	Roster A Yearly	0.004
Roster B Monthly	0.161	Roster B Neighbr	0.039	Roster C Daily	0.003
Roster A Cowork	0.139	Roster B ChineseAm	0.037	Roster C Oceania	0.002
Roster C Monthly	0.137	Roster B Asian	0.029	Roster C Europe	0.002
Roster C Relative	0.130	Roster C Co-worker	0.021	Roster C Asia	0.001
				Roster C NA	0.001

At this stage, the question of how many variables to retain is arbitrary, a decision which is left to the researcher. We retained variables with the top 11 variable loadings which is a cut-off of 0.1 and ensures representation of each roster in each of the top variables. Using this approach, there is a relatively even spread of variables among all three Rosters among the top variable loadings. Taking the top 11 allows for a natural cut-off where there is a "jump" in variable loadings from 0.1 to over 0.13.

Step 2: Clustering

We then cluster these top 11 variables using the **mclust** package and procedure described above. The mclust algorithm is initialized using the Expectation–Maximization (EM) algorithm to find local maxima in the distribution. We first need to initialize the model. In **mclust** this is done by using agglomerative hierarchical clustering and partitioning the data. We do not specify an existing partition, so it is

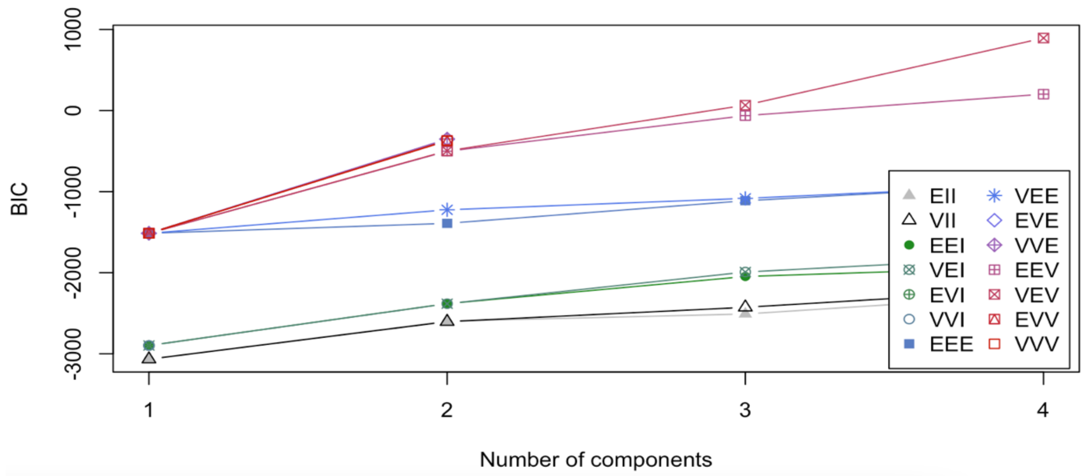

Figure 3: BIC Values at Different Numbers of Components by Model Shape Source, Generated in mclust Package

assumed that each observation is in its own cluster, and then the algorithm iteratively partitions until expectation maximization is achieved.

We start by identifying the optimal Bayesian Information Criterion (BIC) achievable using this procedure. There are several models that can be used for determining this, we focus on the two "ellipsoidal" shaped models which appear to be the best fit for these data, "EEE" (Ellipsoidal, equal volume, shape, and orientation) and "VVV" (ellipsoidal, varying volume, shape, and orientation). We run each with our variables scaled, as well as unscaled. These generate a matrix of merged pairs which we use to initialize the EM algorithm to find the optimal BIC. We then update the BIC by merging the best results. The BIC plot is presented in Figure 3.

The **mclust** package then selects the optimal model based on the BIC identified. We pre-specify the number of clusters can be anywhere from 2 to 4. When we allowed larger numbers of clusters to be selected (5-9), this resulted in multiple small clusters (under 20 individuals) that were not substantively meaningfully different from the larger components. We also do not specify a prior. Future work may want to explore Bayesian implementations of mclust for these purposes. We show 4 clusters are optimal and BIC is optimized using the VEV model, which means components have equal, ellipsoidal shapes with varying volume, and varying orientation. The result is 4 clusters: Cluster 1 with 135, Cluster 2 with 111 individuals, Cluster 3 with 82 individuals, and Cluster 4 with 85 individuals. The figures below show de-meaned proportions for each Roster variable by cluster.

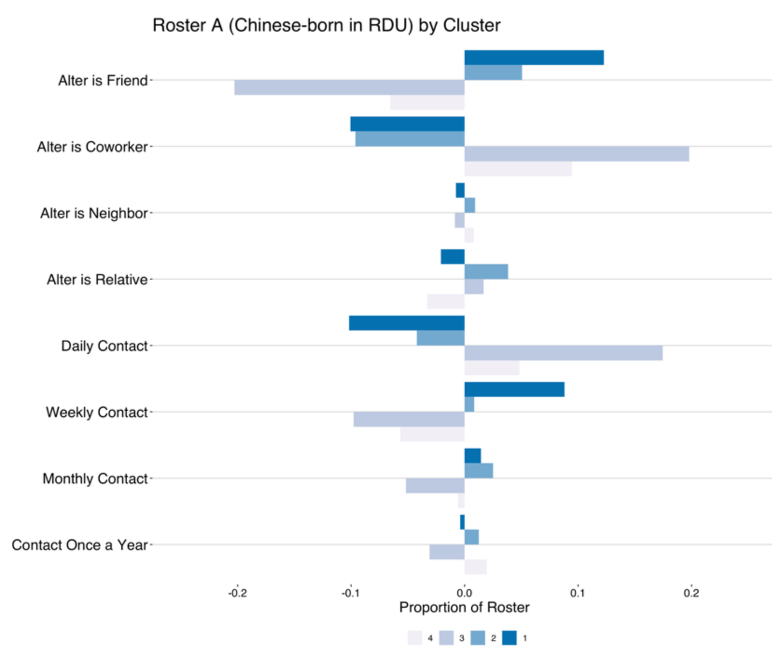

Figure 4: Clustering Results Roster A - Values Are in Proportions of Friends That Meet Criteria on Y Axis. Alter Means Tie, Categories Are Mutually Exclusive

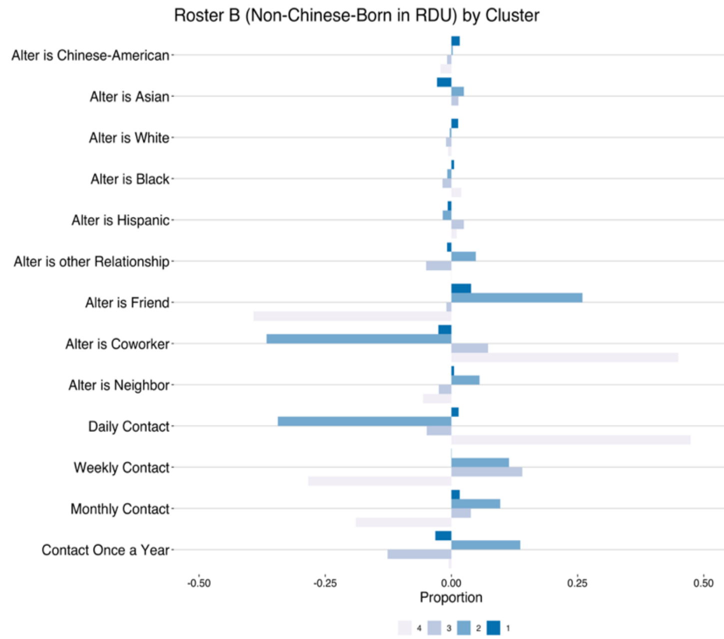

Figure 5: Clustering Results Roster B - Values Are in Proportions of Friends That Meet Criteria on Y Axis. Alter Means Tie, Categories Are Mutually Exclusive

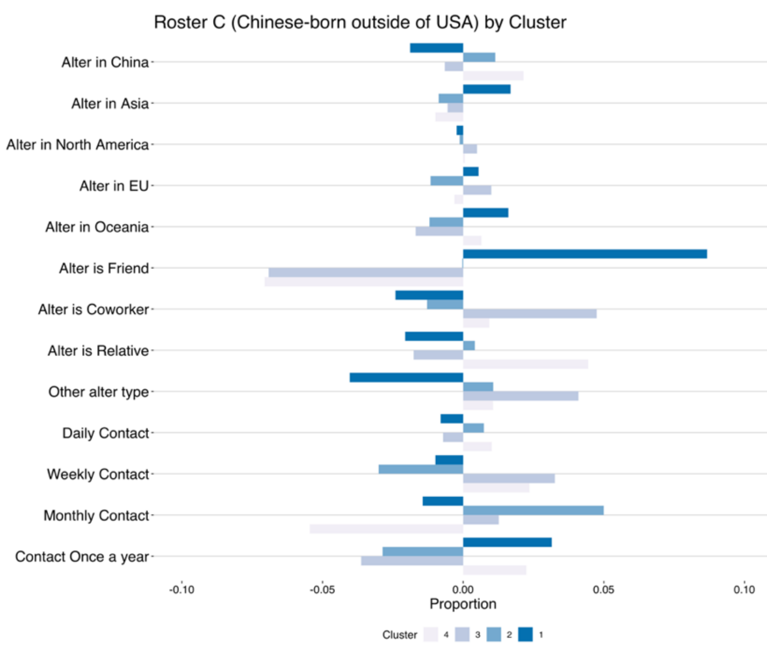

Figure 6: Clustering Results Roster C - Values are in proportions of friends that meet criteria on Y axis. Alter means tie, and categories are mutually exclusive

Table 9: Demographic Characteristics by Cluster: Proportions and Means (S.D.)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Demographics				
Age [18-29]	0.119 (0.324)	0.127 (0.335)	0.146 (0.356)	0.082 (0.277)
Age [30-39]	0.237 (0.427)	0.182 (0.387)	0.378 (0.488)	0.200 (0.402)
Age [40-49]	0.400 (0.492)	0.355 (0.481)	0.244 (0.432)	0.459 (0.501)
Age [50-59]	0.230 (0.422)	0.218 (0.415)	0.207 (0.408)	0.176 (0.383)
Age [60+]	0.015 (0.121)	0.118 (0.324)	0.024 (0.155)	0.082 (0.277)
Female	0.644 (0.480)	0.739 (0.441)	0.585 (0.496)	0.600 (0.493)
Married	0.844 (0.364)	0.847 (0.362)	0.805 (0.399)	0.882 (0.324)
Time in US (years)	13.24 (8.35)	12.85 (10.21)	11.32 (8.71)	14.78 (8.45)
Income 000s (USD)	67.93 (41.69)	52.96 (46.31)	72.53 (54.56)	90.86 (72.66)
Origin				
From Mainland China	0.919 (0.275)	0.874 (0.333)	0.915 (0.281)	0.929 (0.258)
From Hong Kong	0.015 (0.121)	0.009 (0.095)	0.012 (0.110)	0.000 (0.000)
From Taiwan	0.067 (0.250)	0.117 (0.323)	0.073 (0.262)	0.071 (0.258)
Educational Attainment				
High School or less	0.074 (0.263)	0.153 (0.362)	0.085 (0.281)	0.035 (0.186)
Some College	0.111 (0.315)	0.126 (0.333)	0.024 (0.155)	0.047 (0.213)
College	0.178 (0.384)	0.387 (0.489)	0.110 (0.315)	0.176 (0.383)
More than College	0.637 (0.483)	0.333 (0.474)	0.780 (0.416)	0.741 (0.441)
Student/Postdoc	0.148 (0.357)	0.153 (0.362)	0.256 (0.439)	0.118 (0.324)
Currently Employed	0.733 (0.444)	0.441 (0.499)	0.927 (0.262)	0.859 (0.350)
Other Characteristics				
Speaks English Very Well	0.200 (0.401)	0.173 (0.380)	0.220 (0.416)	0.282 (0.453)
Citizen or Green Card	0.793 (0.407)	0.739 (0.441)	0.671 (0.473)	0.835 (0.373)
Has a child over 16	0.394 (0.492)	0.471 (0.504)	0.324 (0.475)	0.409 (0.497)
Belongs to a church	0.504 (0.502)	0.495 (0.502)	0.305 (0.463)	0.318 (0.468)
Owns Property at Origin	0.216 (0.413)	0.261 (0.441)	0.287 (0.455)	0.118 (0.324)
Intends to remain in US	0.615 (0.488)	0.523 (0.502)	0.488 (0.503)	0.659 (0.477)
N	135	111	82	85

Notes: Values in proportions with standard deviation in parentheses. N indicates number of individuals in each cluster.

2.3.3 Results

The results from the clustering process reveal four distinct groups formed on the bases of their networks ties. Figure 4 shows results from Roster A (ties to other Chinese Immigrants in the Raleigh-Durham area), Figure 5 shows Roster B (ties to non-Chinese-born in the Raleigh-Durham Area) and Figure 6 shows Roster C (ties to Chinese-born individuals around the world). It is important to note that relationships between individuals are categorized as mutually exclusive – each tie is classified by the respondent as “co-worker”, “friend”, “relative” or “neighbor”, and thus cannot be both. Previous studies have shown that Chinese immigrant experiences can vary based on origin, language, tenure in the United States, among other demographic characteristics (Keister et al., 2016; Mok & Platt, 2020; Yan et al., 2019). Therefore, in addition to an analysis by network roster, we can also examine demographic variables by cluster. Table 9 shows demographic and basic employment characteristics by Cluster. Here we summarize the network and demographic results by Cluster and define 4 typologies.

Cluster 1: Chinese Friendship Networks

Cluster 1 individuals are the most likely of all clusters to nominate friends in Roster A and have the highest proportion of weekly contact with their fellow Chinese-immigrant nominations of all clusters. While they have a relatively low proportion of daily contact with their ties, compared to the mean, daily contact is associated in our data with being co-workers and not friends. They do not nominate any coworkers in their Roster A connections. Based on this, it appears their level of connection with the Chinese immigrant community is one of closeness and friendship.

Their Roster B nominations are split between co-workers and friends, but they do not stand out on the basis of this roster. For their international contacts in Roster C, they are the most likely of all Clusters to nominate friends, though their contacts are spread out between mainly weekly, monthly and yearly, indicating there is no clear high frequency contact.

In terms of demographics, Cluster 1 individuals are average among all Clusters. The modal age range is [40-49], and the time in US is 13 years on average (nestled between clusters 2 and 4 on this variable). While a large portion, 63.7% of individuals in Cluster 1 have post-graduate education, individuals in this Cluster lag on post-grad degrees to Clusters 3 and 4, as with proportion currently employed.

Overall, Cluster 1 individuals maintain strong co-ethnic ties composed of other Chinese immigrants and contacts with friends outside of the RDU, while having middling nomination of both friends and co-workers in the local non-Chinese immigrant community. Because Cluster 1 stands out by its friendships in Roster A and connections to Chinese-born friends abroad, we call them "*Chinese Friendship Networks*".

Cluster 2: Socially Embedded

Figures 4, 5 and 6 shows Cluster 2 individuals in Roster A are second most likely of all Clusters to nominate friends who are Chinese immigrants and most likely to nominate relatives. Evidence from Roster B results shows these individuals are the most likely of all clusters to be friends with non-Chinese immigrants and have a range of frequency of contact (weekly, monthly and yearly). They do not nominate any coworkers in Roster B, indicating they may not work or only work in Chinese environments. Further, they are the most likely to nominate individuals who are neighbors in both Roster A and Roster B, indicating they may have more time to socialize and become involved with their community.

In terms of demographic characteristics, they are the most likely of all clusters to be women. They are the least educated cluster, with only 33% having post-grad education, the lowest of all clusters, and 15% having high school or less, the highest of all clusters. They are also the least likely to be currently employed (only 44%). Further, they are the second most likely to be members of a church (49%), and the most likely to have children over the age of 16, an indicator that they are raising a family in the US or they came to live with their adult children. They are the most likely of all Clusters to be from Taiwan, though these individuals make up only 11.7% of Cluster 2. In sum, Cluster 2 are Socially Embedded, characterized by a rich social life, especially with non-Chinese born, but not integrated into the non-Chinese immigrant community at work, either because they are at a Chinese workplace or not employed altogether. Their high proportion of friends and lack of co-worker nominations in Roster B is what most distinguishes them from Cluster 1.

Cluster 3: Undecided Newcomers

Individuals in Cluster 3 are the least likely of all to nominate friends and the most likely to nominate co-workers in the Chinese immigrant community in Roster A. Further, they are most likely to have daily contact which is an indicator of a co-worker relationship. This indicates they are less integrated with the local Chinese immigrant community, as it appears they mainly have contacts they deem co-workers instead of friends. They are the second most likely group to nominate co-workers in Roster B (after Cluster 4), though their contacts are split between coworkers and friend. They may work in integrated environments where there are both Chinese and non-Chinese colleagues like the Universities in RDU or the tech industry. They speak with their contacts frequently, half of them on a weekly basis (the rest either daily or monthly). They are the most likely to speak to co-workers outside of the RDU, and the least likely to nominate friends.

They are the youngest of all clusters, with a modal age of 30-39, and are more likely to identify as male than other clusters (though a majority of the sample are women). They have been in the US for the shortest duration and are the most educated of the clusters – 78% have a degree beyond college. They are the most likely of all clusters to be student or postdoc and to be employed (including postdoc employment). Further, they are the least likely to have a child over 16, least likely to hold a Green Card or citizenship, and most likely to own property in China (an indicator of transnational ties or intention to return). Further, they have lowest proportion of respondents that intend to live permanently in the US (around 48%). All of these characteristics are reflective of their younger age and more recent immigration status.

It appears these immigrants are newcomers who have not made their mind up on staying in the US, as evidenced by their ties to China, with low levels of incorporation and high levels of education. We will call Cluster 3 "Undecided Newcomers".

Cluster 4: Economically Integrated

Figures 4, 5, and 6 show that Cluster 4 individuals (light purple) are characterized by nominating a larger portion than average of co-workers who are Chinese immigrants, and a slightly smaller than average portion of friends, though not as few as Cluster 3. They have slightly higher daily contact with their contacts and slightly lower weekly contact than Clusters 1 and 2. In terms of their connections with non-Chinese born individuals, Cluster 4 members are most likely to nominate co-workers and are more likely to speak with their contacts daily. In fact, around 80% of their Roster B contacts are co-workers, the rest are neighbors or other contacts. There is little differentiation among groups in Roster C, though it appears Cluster 4 contacts are most likely to be in China of all clusters, and most likely to be relatives. In sum, their contacts, both Chinese and other, are focused slightly more on the workplace, though they have a balance of Chinese friendship and co-worker networks.

This is unsurprising given their career focus. Individuals in this cluster highly educated (74% have a degree beyond college) and are the second most likely Cluster to be employed (after Cluster 3). They have been in the US for the longest duration. Their incorporation into the local immigrant community as well as connections to co-workers is explained by their time in the US, education levels and employment status. Indeed, they have the highest proportion that speak English *very* well (28.2%) and are the least likely to own property in China.

Given their socioeconomic status characteristics and networks that revolve more around the workplace, Cluster 4 are "Economically Integrated", and they stand out by having daily contact with colleagues on Roster B and both friend and co-worker nominations on Roster A.

2.3.3.1 Linking Chinese Immigrant Typologies With Patterns of Assimilation and Economic Integration

In addition to demographic variables, the ChIRDU study included a rich module on immigrant perceptions of life in the USA and acculturation as well as economic and labor force integration questions. We will broadly call these perceptions of life in the USA and acculturation variables indicators of assimilation, as acculturation is a *pre-cursor to* or *factor in* assimilation (R. D. Alba & Nee, 2003), and economic measures indicators of integration (Schneider & Crul, 2010). This module allows us to uniquely understand how ego-centric networks relate to indicators of assimilation. All variables included in the analysis here are described in Table 7. Indicators of assimilation were regressed on all four clusters without controls to obtain the estimates in Figures 7 and 8.

Figure 7 shows a number of indicators of assimilation across the four clusters of Chinese immigrants. Starting in the top left corner, we see that, compared to Cluster 3, Cluster 1 is 12.6% more likely to report they "miss friends and family abroad" ($p<0.1$). Cluster 1 individuals have been in the United States for a longer duration on average and have more Chinese immigrant and native-born friends compared to Cluster 3, who are the most likely to nominate Chinese immigrant co-workers. Cluster 3 are relative "newcomers", have higher levels of education, higher levels of property ownership in China, and stronger intentions to return to China, showing strong ties with their place of origin. They likely feel that they can return to China (or even plan to) at any time given their position, and therefore miss their friends and family less. This is aligned with findings that cross-border communication decreases with more years spent at destination (Verdery et al., 2018b). Cluster 1 likely communicates less with their connections back home than Cluster 3, which could lead them to miss their friends and family. Indeed, we know from Roster C that Cluster 3 individuals speak with their Chinese friends and family outside of the RDU the most (mode of weekly), and Cluster 1 speaks with them the least (mode of yearly).

In the next graph, "Wants to adapt to the USA", we see that Cluster 2 has a 15% greater likelihood of wanting to adapt than Cluster 4 ($p<0.05$). This may appear surprising at first glance, considering Cluster 2's lower education and lower employment level. However, Cluster 2's networks, which include friends inside and outside the immigrant community, indicates a willingness to adapt to the USA, despite their lower SES. However, it could be that they are married women in single-earner households, or that their job is supplementing a larger household income, and thus their household SES is not low. This would be consistent with Alba and Nee's theory assimilation and the first pathway of segmented assimilation, which is associated with joining the "white" middle class through acculturation (R. D. Alba & Nee, 2003; R. Alba & Nee, 1997; Portes & Zhou, 1993; Zhou, 2014). However, existing frameworks typically equate achievement and educational attainment with assimilation, especially for Asian Americans (R. D. Alba & Nee, 2003; Portes & Zhou, 1993; Sakamoto et al., 2009). However, when Asian Americans, or even Chinese Americans, are taken as a whole, groups like Cluster 2 get ignored due to their relatively lower education and income but integrated networks. We therefore find that their networks show social "assimilation" in the Raleigh-Durham community, but perhaps not economic assimilation (though their household income is unknown).

In the next graph, "Identify Completely or Partly as American", we find that Cluster 4 individuals are the most likely to identify at least partly as American compared with all other clusters, and this difference is statistically significant from Cluster 3 (19.4% more likely with $p<0.05$) and Cluster 1 (12.1% more likely with $p<0.1$).

Indeed, Cluster 4 individuals have the highest duration in the Unites States, are the most likely to be Green Card holders or citizens, have the highest levels of English ability and appear to have higher income jobs. In our analysis, they are more likely than others to have networks that were formed at the workplace, an indicator they are career focused. Therefore, achievement and high SES may be the most salient aspects of their social identity, which they may see as markers of American identity, leading Cluster 4 then to identify as partly American. While it is perhaps counter-intuitive that a cluster characterized by embeddedness in Chinese networks are more likely to identify as at least partly American, this is in line with findings that immigrants, especially those from China, use their co-ethnic ties and belonging to assimilate (Portes & Zhou, 1993; Zhou, 2014). Indeed, Zhou (2014) shows that strong community support among co-ethnic Chinese and Chinese Americans is key to achieving assimilation outcomes.

Further, it is unsurprising that Cluster 3 has the lowest likelihood of identifying as American or partly American. The representation of students and postdocs is highest for this group, they have been in the U.S. for the shortest duration, and they are the most likely to hold property in China, and they are the least likely to say they want to stay permanently in the US, indicating they are maintaining strong connections to their country of origin.

Taken together, Cluster 3 and 4 do present somewhat of a puzzle. Most of the literature on how lived experience affects ethnic identity comes from Latin Americans in the US and shows that perceived discrimination *reinforces* ethnic identity (Golash-Boza and Darity 2008, J. C. Lee and Kye 2016). However, Cluster 3 and 4 both perceive similar levels of relatively high discrimination (see results below, for example, on "Americans Feel Superior"), yet express different levels of American identity. This lends credence to the idea that, for Cluster 4, socioeconomic status is a more important aspect of their achieved identity, based on their achieved SES in the US, which they associate with their identity as at least partly American.

In the next graph on the right, we compare responses on where there is "No Better Country than the USA". We do not find any significant differences in this variable by cluster. It is worth noting that across all clusters, the average value for this variable is quite low, hovering below 25%.

The final graph in the top right compares clusters on whether they believe life in the USA weakens the family. On this measure, Cluster 3 and 4 rank about 10% higher than Cluster 1 ($p<0.1$). Cluster 3 and 4 are similar in that they nominated an above-average portion of co-workers in Rosters A and B – unlike Clusters 1 and 2 who nominated an above-average portion of Chinese immigrant friends. It may be that these more socially integrated clusters, 1 and 2, simply have more exposure to other people's family life because they have more "friends" on average than Clusters 3 and 4. Clusters 1 and 2 are the most likely to attend a church (around 50% of each cluster). Because churches reinforce family values, they may be more exposed to “strong-family” messaging in the USA than their counterparts in other clusters.

We see no statistically significant difference on either of the graphs in the bottom left “There is racial discrimination on opportunities in the USA” or “There is a conflict between ethnic groups in the USA”. Future work will seek to understand this null result in line with measures of everyday discrimination, which were collected as part of ChIRDU.

The next graph to the left shows whether respondents are more likely to feel that Americans feel superior to them. Cluster 2 individuals are less likely to feel this way than those in Cluster 3 and 4 ($p<0.1$). This is likely due to the fact that Cluster 2 networks and demographics show they are lower SES and more socially integrated into non-Chinese networks therefore are less protective of their status, and likely less concerned how they are perceived by Americans. (2) Clusters 3 and 4 are highly educated with high English levels– they may feel they are not receiving due respect in American society (Chou & Feagin, 2015). These indices of acculturation (like English level) make them more aware of discrimination, and thus may be more likely to perceive that Americans feel superior (Finch & Vega, 2003). Indeed, Wiley et. al show that there is a strong association between public perceptions of ethnic identity (In general, others respect _______) and private perceptions of identity (In general, I’m glad to be a(n) _______) among 49 first generation Asian Pacific Islanders, mostly Chinese and Indian

(Wiley et al., 2008). This adequately explains the correlation between Cluster 3's self-identification as Chinese (not American), and perception that Americans feel superior, and Cluster 2s higher proportion identifying as American, on average.

The final variable sums all measures of assimilation shown here, ("There is no better country than the USA", "Life in the USA weakens family" (reverse coded), "There is racial discrimination in opportunities" (reverse coded), "There is conflict between ethnic groups in the USA" (reverse coded), "Non-whites have as many opportunities to get ahead economically as whites in the U.S.", and "Americans feel Superior" (reverse coded). We find that Cluster 2 is more satisfied with life in the USA than all other Clusters, statistically significantly more so than Cluster 1 ($p<0.05$) and Cluster 3 ($p<0.05$). This is not surprising given that Cluster 2 was less opposed to life in the U.S., and more willing to acculturate and have native networks. Further, they were less likely to say there was racial discrimination in opportunities in the US, less likely to say there was conflict between ethnic groups and more likely to say there were opportunities for non-whites in the USA, though none of these differences were statistically significantly different from those of other clusters. Indeed, Cluster 2, as the lowest education and lowest proportion employed group may perceive less inequality of opportunity because they are less likely to have competed for jobs with local white individuals. Because they interact less with Americans in the workplace, they may also be less likely to encounter discriminatory behaviour where they perceive Americans feel superior. These factors combine to create a higher score in Satisfaction with Life in the USA for Cluster 2.

2.3.3.2 Economic Integration Results

Figure 8 shows a variety of work and income variables which help us understand the economic and employment integration of Chinese immigrants in the Raleigh-Durham area. Similar to the descriptive statistics for current employment in Table 9, we find members of Cluster 2 less likely to have ever worked in the US than members of Clusters 1 ($p<0.001$), Cluster 3 ($p<0.001$) and Cluster 4 ($p<0.001$). Further, Cluster 1 is less likely to have ever worked in the US than Cluster 3 ($p<0.001$) and Cluster 4 ($p<0.05$). Indeed, this is reflected by the social networks of members of each Cluster. Cluster 2 nominate nearly 0 co-workers across rosters (and far below average levels), indicating they are either not working, or are more embedded in friendship than co-worker networks. Members of Cluster 1 are the second-most integrated into the non-Chinese-born community and are more likely to nominate friends in Roster B compared to Clusters 3 and 4. It is also worth noting that these two groups are more likely to be women. Indeed, gender is believed to play a role in the integration of Chinese immigrants. Asian women in the US have lower returns to education than men, which may be reflected here in their overall employment status (Flippen & Kim, 2015).

Cluster 2 members work significantly fewer hours than their counterparts in other clusters, less than up to 7.0 weekly hours when compared to Cluster 4 ($p<0.001$).

They are also more likely to work in Chinese environments (given by percentage of Chinese employees in their workplace), are more likely to be paid on an hourly basis compared to Cluster 4 ($p<0.1$). Indeed, this is broadly reflected in their personal networks, which are the least likely of all to be composed by non-Chinese-born co-workers, and the most likely of all to be composed by local Chinese-born relatives and friends. These individuals are largely female, married, and the lowest educated of the clusters. It is thus not surprising that they score lower on economic indicators of status.

From Figure 8, we observe that Cluster 4 individuals are the least likely to own a business (be self-employed), and that this is significantly lower than business ownership for Clusters 1 (10% higher with $p<0.1$), 2 (14% higher with $p<0.05$) and 3 (17.0% higher with $p<0.001$). Indeed, Cluster 3's relatively high proportion of business owners aligns with their overall profile: highly educated and perhaps poised to create a start-up in tech or pharma especially considering the context of Raleigh-Durham, which is a hub in these industries. While previous work on assimilation has argued that ethnic enclaves provide environments that are ripe for immigrant entrepreneurship (Achidi Ndofor & Priem, 2011; Portes & Jensen, 1989), it is premature in their migration history to say whether Cluster 3 individuals are benefiting from this environment. It appears instead that they are drawing on their own attributes to achieve success, regardless of ethnicity, which would support the theory of new assimilation (R. D. Alba & Nee, 2003).

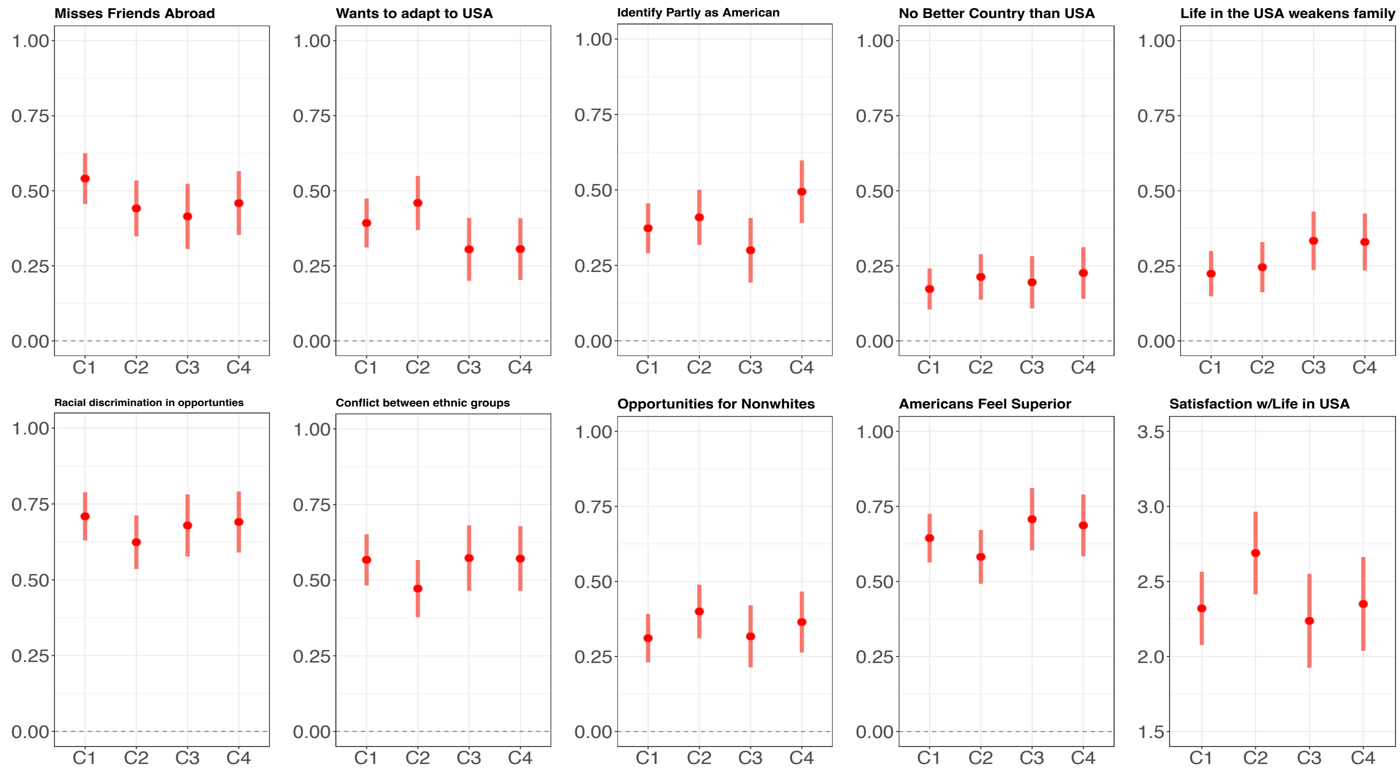

Figure 7: Indicators of Assimilation by Cluster

Notes: Values are coefficients from linear models with Cluster as the main independent variable and without controls. Values coded either 0 or 1, for Agrees (1) or Disagrees (0) with statement. Means in Table 7. Scale of Dissatisfaction obtained by summing: “There is no better country than the USA”, “Life in the USA weakens family” (reverse coded), “There is racial discrimination in opportunities” (reverse coded), “There is conflict between ethnic groups in the USA” (reverse coded), “Non-whites have as many opportunities to get ahead economically as whites.”, and “Americans feel Superior” (reverse coded).

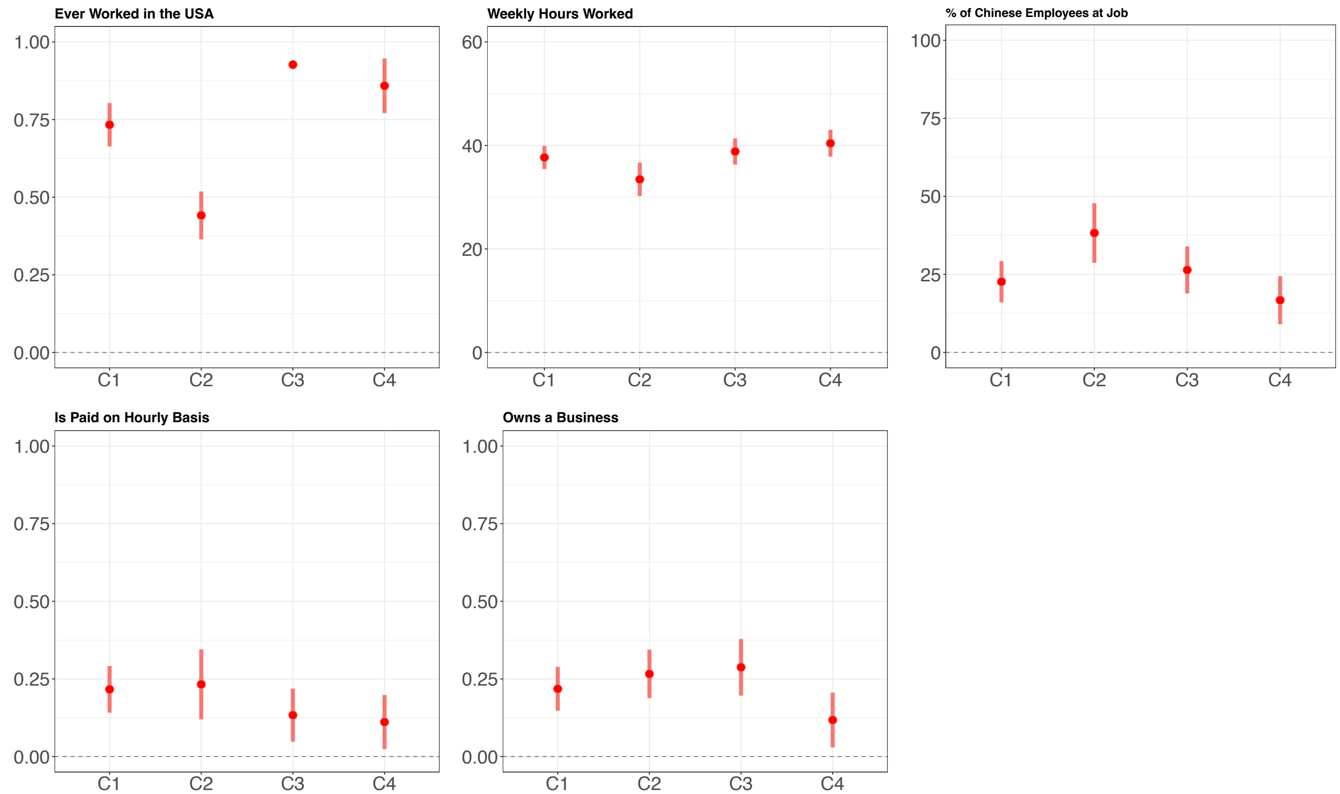

Figure 8: Work and Income Indicators

Notes: Values in graphs are coefficients from linear models with Cluster as the main independent variable and without controls

2.4 Discussion and Conclusion

This paper sought to classify Chinese migrants in a new destination according to their networks. We first answered Question 1 posed in the introduction: How many types of immigrants can we identify, and Question 2, What do these types look like? Using a clustering procedure employing Gaussian mixture models, we identified 4 typologies: *Chinese Friendship Networks*, *Socially Embedded*, *Undecided Newcomers* and *Economically Integrated*. Although the clustering was performed on network variables, these clusters are ultimately distinguished both by their personal networks and their demographic characteristics.

Next, we sought to understand how these typologies are related to existing assimilation frameworks (Question 3) and whether there is any correlation between clusters and indicators of assimilation (Question 4). The four assimilation frameworks that we focus on here are: Transnationalism, Social Networks, Assimilation Theory and Segmented Assimilation.

Local social networks at destination, the backbone of social network theories of assimilation (Lancee, 2012; Lubbers et al., 2007; Ryan et al., 2008), vary widely among clusters. Indeed, we can identify whether immigrants are more integrated into the local community via their co-national ties, or ties to non-Chinese-born, as well as the nature of those ties. These findings dovetail with predictions from assimilation theory and segmented assimilation theory, thus we examine these theories in tandem.

Cluster 1, *Chinese Friendship Networks*, are characterised by their embeddedness in local Chinese immigrant networks in RDU, nominating friends in Roster A more than any other cluster, and maintaining relatively frequent contact with their Roster A connections. They are the most likely to "Miss Friends Abroad" and most likely to attend church, and are otherwise middling on demographic and employment characteristics. The importance of local co-ethnic friendship networks has been an important lynchpin of assimilation research on Asians and second-generation Asian Americans since earlier works on ethnic enclaves. Segmented Assimilation proponents, in particular, emphasize the importance of maintaining ethnic identity for assimilation in their "third pathway" (Portes & Zhou, 1993). Indeed, these local friendship networks have been called out as a factor in the success of Asian and Chinese first and second-generation immigrants, because these networks provide resources and support to their members (Kasinitz et al., 2009). However, our findings here show that there is great heterogeneity in how networks shape factors of both acculturation and economic integration.

While Cluster 1 is the cluster that seems to maintain the strongest ties to the local Chinese community, they are not the most "successful" in terms of income or education, compared to Clusters 3 and 4. They also have, for example, lower Satisfaction of Life in the USA than Cluster 2. This reveals an important heterogeneity in how immigrants use their networks, and how "protective" local immigrant networks may be against feelings of discrimination or general hurdles in acculturation. For example, maintaining strong ties to the Chinese community at home and abroad may be the reason Cluster 1 misses their friends and family outside the RDU more than other Clusters. This is not to say that local networks are harmful for assimilation indicators, by most measures Cluster 1 shows evidence of high achievement, but instead to show that within this highly educated highly employed immigrant population, there is heterogeneity in local tie formation.

Cluster 2, *Socially Embedded,* are the most likely of all to nominate local non-co-ethnic networks mainly composed by friends who are white. They also have regular contact with these friends. They are distinguished from Cluster 1 in that they do not nominate any co-workers local non-Chinese born contacts and nominate fewer friends on average than Cluster 1 in Roster A. We find that this may be attributed to the relatively low employment rate of Cluster 2 individuals.

This integration into majority networks is typically associated with assimilation or integration that would predict employment and economic success (Lancee, 2012; Ryan et al., 2008). This is clearly outlined in Alba and Nee's assimilation theory, who define assimilation as a process by which ethnicity declines in relevance in increasingly more aspects of life (R. D. Alba & Nee, 2003). In the case of Cluster 2, nominating friends outside of the Chinese community indicates this is one aspect of their social life where ethnicity is less relevant. Their indicators of acculturation, as part of the assimilation process, reflect this as well. Cluster 2, more than others, want to adapt to the USA and have greater overall satisfaction. This aligns with their more American social networks. In a segmented assimilation framework, Cluster 2's situation is most aligned with the "first" pathway, which involves acculturation to the white, American, middle-class society (Portes & Zhou, 1993).

However, there remain some puzzles with regards to Cluster 2's assimilation patterns. Firstly, they have the lowest English levels of all clusters, which is considered an important marker of assimilation in both assimilation and segmented assimilation theories (R. D. Alba & Nee, 2003; Portes & Zhou, 1993). Further, "mainstream" assimilation is often directly associated with socioeconomic parity with the majority group (R. Alba & Nee, 1997). While we do not examine that directly here, we do note that Cluster 2 has the lowest income and educational levels and higher likelihood of getting paid on an hourly basis. However, it is possible that low employment and low income among Cluster 2 individuals is masking well-off, single earner households where Cluster 2 individuals are the trailing spouse, or the cohabitating parent of an adult immigrant child. It may also be the case that Cluster 2 is concerned with social-desirability of their answers, which may prompt them to indicate they want to adapt to US society. If we did not have any network data, based only on socioeconomic and demographic characteristics, it is unlikely we would have categorized Cluster 2 as mainstream assimilated, and they do not fit this category perfectly. However, having access to network data has allowed us to understand an important aspect of Cluster 2s immigration experience and unmasked an often-overlooked aspect of assimilation, friendship networks.

Cluster 3, *Undecided Newcomers*, have relatively low connection to both co-ethnic and non-co-ethnic locals in the Raleigh-Durham area, nominating mostly co-workers, particularly in Roster A. This is explained by the fact that they are relative newcomers, a quarter of whom are students or postdocs, and within that category, most are students. In terms of their ego-centric networks, they display low social integration. They are the most likely to own property in China, and the least like to want to stay in the US. In this case, the lens of assimilation would suggest very low assimilation, and there is no corollary in theories of segmented assimilation, in part because these theories explain assimilation for second generation immigrant groups. Indeed, this cluster is the most likely to identify as only Chinese. Importantly, this cluster has other markers of assimilation: high socioeconomic status, the highest educational attainment, the second highest levels of English. This highlights the complexity of measuring assimilation, and how things like immigration intent should factor into understanding the immigrant experience.

Similarly, Cluster 3 individuals show multiple markers of transnationalism, but because of their temporary and undecided nature, how they fit into traditional theories of transnationalism is unclear. Some have noted that cross-border contact including international travel is a feature of transnational immigrants, though this is framed as a means to achieving success as an entrepreneur or in specific fields, and thus would not necessarily apply to foreign students (Portes et al., 1999, 2002). Further, Cluster 3's level of attachment to China is likely a result of having been in the US for a relatively low number of years, and only time will tell whether they will continue to live transnationally, return to their home country, or slowly cut ties as they incorporate, as predicted by Waldinger (2015).

Lastly, Cluster 4, *Economically Integrated*, appear to have multiple markers of "mainstream assimilation", high levels of employment, high income, employment in predominantly non-Chinese firms, good mastery of spoken English (well or very well) (R. D. Alba & Nee, 2003; Zhou, 1997). Indeed, their networks are mainly formed at work- both among Chinese-born and non-Chinese born contacts. However, they have especially low embeddedness into the local, non-Chinese-born community, nominating the fewest friends of all in Roster B, and nominating a middling proportion of friends in Roster A. This profile aligns best with the "third" group from the segmented assimilation framework, immigrants who experience economic advancement while maintaining home-culture and immigrant solidarity (Portes & Zhou, 1993). Indeed, Chinese immigrants that stay connected to the Chinese community are able to access resources to improve their educational, occupational and social outcomes (Kasinitz et al., 2009; J. Lee & Zhou, 2017; Zhou, 2014).

However, this has not protected them from concerns that, for example, Americans feel superior, which may signal feelings of discrimination. Lee and Kye (2016) propose a relevant framework of *Racialized Assimilation* relating specifically to Asian Americans. In sum, despite the achievements of Asian Americans in recent decades, they continue to face racial subordination and thus their race is a limiting factor in their high-status attainment. Indeed, Cluster 4 individuals who have achieved high SES, a secure legal status in American society and a partially American social identity may feel most the effects of their racialization, compared to, say, Cluster 2 who has a lower SES. Indeed, Lee and Kye call for a shift away from examining merely "socioeconomic accomplishments" (p. 267) which may mask the assimilation patterns of a group like Cluster 4, relatively secure but still facing lower satisfaction with their life in the USA than other clusters.

In disaggregating Chinese immigrants by type, we are contributing to the literature on the process of assimilation, which is heterogeneous and often masked when racial and ethnic categories are treated as homogenous (Drouhot & Garip, 2021). Existing assimilation frameworks are useful lenses through which to interpret the Chinese assimilation experience, as shown here (R. D. Alba & Nee, 2003; R. Alba & Nee, 1997; J. C. Lee & Kye, 2016; Portes et al., 1999; Portes & Rumbaut, 2001; Portes & Zhou, 1993). However, they are formulated to describe averages across countries of origin and migration experience which inevitably will leave out certain immigrant trajectories.

When looking at the four types of Chinese immigrants we uncovered in the Raleigh-Durham area by clustering on social networks, we find Cluster 2, lower SES than the rest but embedded in the local non-Chinese community, difficult to place within existing frameworks. Cluster 3, characterised by its international student body, is not a clear case of transnationalism by virtue of their return intentions, and Cluster 4 is best viewed through the lens of racialized assimilation. As more work focuses on breaking down existing categories of immigrants, it is likely that new, more granular frameworks will be required to understand the multitude of migrant assimilation patterns. In this paper, we show that social networks are an important differentiator of the migrant experience and should be incorporated more explicitly into assimilation frameworks moving forward.

Several issues limit the more general interpretation of our results. First, the Raleigh-Durham area is relatively unique. It is a new destination, attracting highly educated immigrants working in tech, semiconductor, pharmaceutical, and academic industries. Immigrants in our sample have been in the US for fewer than 20 years on average, meaning there is no long-standing and established Chinese community, compared to more traditional receiving areas like New York (Kasinitz et al., 2009). Therefore, these results may be most useful when thinking about the process of assimilation of recent cohorts of Chinese immigrants in destinations where the community is new, educated, and suburban, but not necessarily communities with long histories and a broader mix in terms of socioeconomic status.

Second, by virtue of the sample recruitment strategy, this sample is a linked sample which by default will exclude individuals who are isolated or otherwise without ties to the Chinese community. In this case, we would be omitting a cluster of individuals that are "unconnected" on one hand or, on the other hand, so "mainstream assimilated" that they have retained no connections to the Chinese community. Future work on Chinese immigrants in new destinations can hopefully shed light on the full range of network typologies through different methods of data collection.

Given that existing research on Chinese immigrant assimilation has not adequately considered the role of personal networks (Flippen & Kim, 2015; J. C. Lee & Kye, 2016; Lueck, 2018; Zhou, 2014), this paper has brought together understandings of personal networks and assimilation frameworks to understand Chinese migrant incorporation with a new lens. We build on research that explores immigrant typologies (Brandes et al., 2010; Lubbers et al., 2007; Vacca et al., 2018) which allows us to group immigrants on the basis of their networks and compare different types.

3. To Help… Or Not To Help?

3.1 Introduction

Support from peers is essential to finding work. Individuals rely on colleagues, friends, and acquaintances to help them navigate job markets by providing job referrals, advice on writing a resumes and cover letters, and strategies to succeed in the application process (Fernandez & Weinberg, 1997; Smith & Young, 2017; Vacchiano, 2021). This type of support would seem crucial to the success of immigrants, who have been shown to rely deeply on their networks as they transition to life in a new country (Aguilera, 2005; Aguilera & Massey, 2003; Pfeffer & Parra, 2009). Immigrants tend to perceive lower costs to moving to destinations where they already have friends and family (Boyd, 1989; Garip & Asad, 2016; Massey, 1986; Merli et al., 2021; Palloni et al., 2001). Moreover, immigrants lend each other support in terms of housing (Menjivar, 1997), information about welfare programs (Bertrand et al., 2000), accessing healthcare (Deri, 2005; Devillanova, 2008), and the job market (Aguilera & Massey, 2003). Yet despite the wealth of evidence highlighting immigrants' dependence on networks to adjust to their new context, little is known about when and why other migrants are willing to help newcomers find work. This paper seeks to fill this gap.

One prominent answer points to the role of ethnic solidarity in helping migrants find jobs: individuals tend to help their co-ethnics or co-nationals find jobs. There is some support for this view. Scholars have shown that co-ethnic hires are perceived as less risky than local hires because they come through networks and are likely to have previous contact in industries that comprised ethnic niches (Bailey & Waldinger, 1991). Others show that ethnic minorities hire each other to maintain a dominant position in a niche industry (Jiobu, 1988). Yet a fundamental assumption remains untested: does ethnic solidarity generally lead to provision of help to immigrants of the same origin (Portes & Manning, 1986; Portes & Sensenbrenner, 1993; Portes & Shafer, 2007)? Recent works cast doubt on this assumption, that ethnic solidarity always leads to intra-ethnic support, highlighting the role of competition and reputational risk. For instance, a study of Polish immigrants to London found that information about jobs was withheld when there was a perceived competition for scarce jobs in the Polish community (Ryan et al., 2008). In a study of black, urban, poor individuals in the US found that over 80% of the sample were reticent to lend any job support due to job seekers being too needy, too unmotivated, or prone to delinquency, indicating that racial solidarity may not always prevail (Smith, 2005). These two examples show that ethnic solidarity *may not* be the dominant factor in job referral decisions for immigrants.

Networks permeate most domains of an immigrant's life, therefore it is likely that whether or not a migrant decides to give a referral is moderated by the characteristics of the tie to the job seeker. Because immigrants are both *source of* and a *seeker of* help in the job market, the relationship between immigrant networks and job support is an indicator of how immigrant populations are finding work. In this study, we shed light on the circumstances under which ethnic solidarity in migrant social networks prevails, and when it falls apart.

We accomplish this using vignette experiments run online among two different samples of individuals who are immigrants to the United States from Latin American countries or Puerto Rico and who have ever worked in the United States. Across three vignettes, the experiment randomizes levels of reputational risk posed by the jobseeker, tie strength between job referrer and seeker, labor market competition levels, and whether the connection between seeker and referrer is local or transnational. In using random assignment, observable characteristics like gender, age, and country of origin, and unobservable characteristics like altruistic nature or motivation of participants are balanced across groups. This allows us to obtain causal estimates of the relationships between key independent and dependent variables, among a population that has undergone the job search process as an immigrant.

First, we identify the amount of consideration given to *reputation* when a person is considering whether to give another person a referral or other job support. We find that when a candidate poses a reputational risk to their referrer or supporter, they are significantly less likely to receive support. Second, we test whether the co-ethnic bond acts as a mediator between reputation and likelihood of giving job search support, such that co-ethnic or home-country connection can reduce or eliminate the effect of a risky candidate. We find support for this hypothesis in one sample but the opposite effect in the second sample. Third, we test whether immigrants will be less likely to offer support to individuals in their own migrant ethnic group in a competitive environment (versus a non-competitive one). We find some support for this, but cannot reject the null hypothesis due to lack of statistical significance. Fourth, we examine the effect of tie strength (close friend versus stranger) on the likelihood of offering job support in a situation where there are few jobs available, a competitive environment. We find a positive effect of tie strength on job support. Lastly, we test whether the existence of a co-ethnic or home-country connection interacts with tie strength to lead to a higher likelihood of offering support in a competitive environment. This hypothesis is supported, and we find evidence of an interaction effect between type of tie and strength of tie on job support such that being a close friend leads to a greater likelihood of giving job support when there is no immigrant connection, but this tie strength effect disappears for individuals from the same home country.

This paper advances the literatures on immigration, job search, and networks along two lines. First, by challenging the notion that ethnic solidarity always pushes in the same (positive) direction (Portes & Manning, 1986; Portes & Sensenbrenner, 1993; Portes & Shafer, 2007), we call for the reformulation of public policies aimed at helping migrants integrate into their new environments. Dropping an immigrant into an ethnic enclave isn't enough. Lack of a referral or search support can leave the most vulnerable immigrants jobless, and understanding these patterns can help policymakers and nonprofits shift their resources to target immigrants that might need the most help (Le Barbenchon & Keister, 2021). Second, we advance the literature on social capital among immigrants and show that immigrant networks may create both opportunities and challenges for individuals to mobilize their ties and use these network resources to find work.

3.2 Theoretical Background

3.2.1 Job Searching and Networks

Individuals often draw on their social ties to obtain employment (Castilla et al., 2013; Granovetter, 1973; Marsden & Gorman, 2001), whether or not they are actively looking for work (McDonald & Glen H. Elder, 2006). Those who use their contacts to find jobs can often find better suited employment for their skills, find out about unadvertised opportunities, or find employment more quickly at lower cost (Aguilera, 2002; Calvó-Armengol & Jackson, 2004; Montgomery, 1991). However, wage or prestige outcomes may be correlated with an individual's network. For example, people with higher valued skills may be connected to people with high incomes, making it unclear whether there are causal links between networks and job outcomes or it is merely an artifact of the data (Mouw, 2003).

Understanding the job referral intentions of individuals is particularly difficult to capture, in part because it involves understanding inaction or unwillingness to help as well as willingness to do so. Previous literature on job referrals has focused most on individuals actively job searching, with little attention paid to the role of social capital in job switching that does not involve a search (McDonald, 2015). Furthermore, most of the literature on job searches have been from the perspective of the searcher (Lancee, 2012; Mouw, 2003) and do not use network data. Of those that have looked at the job referrer (Marin, 2012; O'Connor, 2013; Smith, 2005; Smith & Young, 2017), none have looked uniquely from the perspective of a migrant community, which has a particular social structure that rely more heavily on co-ethnic support (Nee et al., 1994).

Theories of social capital can help elucidate the dynamics of job referrals from the referrer side. According to network definitions of social capital, individuals are embedded in social networks which may help them access resources or information to, for example, find jobs (Burt, 2000; N. Lin, 2008). Social capital engenders outcomes that can be beneficial to the individual who is seeking a job via four mechanisms: (1) information transfer; (2) influence on agents that may help the individual access employment; (3) social credentials which provides assurance to employers; (4) reinforcements of one's identity and belonging as a group member (N. Lin 1999). The mechanisms of social capital are also beneficial to the individual *offering* support: the latter are typically subject to community norms that expect them to help others, and in return they receive appreciation from their group (Portes, 1998). However, if an immigrant's social ties are not willing and able to provide help, they are of little use in the migrant's job search (Smith, 2005). This is the distinction between accessed capital, social capital that is merely available through an individual's networks, and capital that is *mobilized* through explicit use of contacts (N. Lin et al., 2001; Smith, 2005).

In addition, the structural features of a network are important in the delivery of resources and information to individuals. Notably, social closure, where everyone in the network is connected to one another, is an important feature of networks where there is trust and reciprocity present. Closure occurs in denser networks where there is more social monitoring (Coleman, 1988). For example, in a close-knit migrant community, there may be expectations of reciprocity and help, and members of the network who do not provide this support are likely to be socially sanctioned.

3.2.2 Immigration and Ethnic Solidarity

Immigrants use their social networks to seek information about when, where and how to access social and labor market opportunities upon arrival (Durand & Massey, 1992; Massey, 1986, 2004; Massey & Espinosa, 1997; Palloni et al., 2001). Social networks have been shown to be instrumental to newly arrived immigrants in obtaining jobs and getting better job matches (Aguilera & Massey, 2003; Lancee, 2012; Ryan, 2011; Ryan et al., 2008). Previous studies show migrants also tend to be connected to individuals from their region of origin, though this may be an artifact of existing data (Durand & Massey, 1992).

While networks may be formed at destination, this process is linked to ties that existed pre-migration (Ryan, 2011). To use an example, an immigrant may form ties with other immigrants at destination because they share a mutual contact in their home country, which will in turn affect their social networks and could impact their incorporation into the community. However, much of the literature on immigrant incorporation has relied on immigrant personal ties among household members at origin and destination while ignoring ties that are transnational but may bind individuals at destination, such as friends at destination of a family member at origin (Aguilera, 2005; Aguilera & Massey, 2003). Other recent works have expressed the importance of ties between origin and destination to explain migrant behavior and integration, showing, for example, that increased contact with friends back home has been associated with a decreased desire to obtain permanent residency among Mexican immigrants in the US (Beauchemin, 2014; Mouw et al., 2014). However, this research does not focus on how immigrant integration may rely on connections to individuals that were made before migrating.

Beyond inter-personal connections of migrants, there has been a large literature on migrant social capital through the lens of ethnic enclaves. While ethnic enclaves were typically defined as geographic areas of ethnic business concentration (Portes & Jensen, 1989), much of this literature has also pointed to co-ethnic hiring as an important feature of ethnic enclaves (Bailey & Waldinger, 1991; Jiobu, 1988; Portes & Bach, 1985; J. Sanders et al., 2002; J. M. Sanders & Nee, 1987). Immigrants who live in an enclave have been shown to find better matched work thanks to information sharing (Damm, 2009). This topic has been motivated most frequently by the concept of ethnic solidarity, whereby there exists an intangible social capital for co-ethnics simply by virtue of belonging to this group.

Ethnic solidarity in migrant communities has been shown, particularly in the case of Cuban migrants to Miami, to play an important role in access to credit and financing, access to jobs and social integration support, all of which are typically difficult for newcomers without connections (Portes & Sensenbrenner, 1993). Furthermore, there is experimental evidence that individuals are more likely to provide support to others in their ethnic group, and that this is not merely attributable to the degree of social distance among members of the same ethnic group (Baldassarri & Grossman, 2013).

Still, while the link in the literature between ethnic groups and providing intra-group support is clear, the case of immigrants presents an additional layer of complication. Immigrant social networks often have different structures and properties than non-immigrant networks (Portes, 1998, 2000; Rostila, 2010; J. Sanders et al., 2002). Notably, they are more likely to be characterized by "closure", a feature of a network that occurs when friends of an individual are friends with each other (Coleman, 1988). Indeed, closure is more likely to occur in small, dense networks, where ties overlap (Coleman, 1988; Smith, 2005). As immigrants form their networks at destination, mainly with other immigrants (Chuatico & Haan, 2020; Wimmer, 2004), these networks are often dense with overlapping ties (Lubbers et al., 2007, 2010), indicating higher social closure (Coleman, 1988).

Network without social closure **Network with social closure**

Figure 9: Example of Networks With and Without Social Closure

This type of network enables the enforcement of social norms through social monitoring. In the image above on the right, for example, nodes B, C and D can "combine forces" to effectively sanction any undesirable behavior of node A, which would not be possible on the graph on the left, because B, C and D do not know each other. Social closure also allows for the reinforcement of positive behavior as the structure allows information about node behaviour to flow through edges (Coleman, 1988). These collective sanctions facilitate trust in the network, and thus allow individuals to build and maintain their reputation (Coleman, 1988).

Per this theory, in dense immigrant networks, social monitoring may lead to increased likelihood of job referrals considering the social benefits that accrue to individuals who are seen helping others in the community (Portes, 1998). However, cases of social monitoring make reputation and competition more salient, which could reduce supportive behaviour in a group in certain circumstances (Putnam, 2007; Ryan et al., 2008; Smith, 2005; Smith & Young, 2017). Hypothesis 1 stems from the literature on ethnicity and migrant solidarity in ethnic enclaves as a primary driver of intra-ethnic support:

Hypothesis 1 (H1): Individuals are more likely to provide job search or referral support to individuals in their own migrant ethnic group than those in other groups, all else being equal.

Existing scholarship on the referee side of the referral dyad, although rarer, provides some evidence that individuals do not always share information about jobs or provide referrals to members of their networks. In a study of black urban individuals, 75% based their decision on whether to provide a referral on the reputation of their referees (Smith, 2005). Individuals that were more entrenched in their jobs and roles were more likely to be open to offering help, as they felt they had less to lose as they had already built up their own reputation (Smith, 2005). People may not refer unemployed job seekers for reputational reasons (Bond & Fernandez, 2019). Reticence to refer can come from cultural logics that make individuals risk averse and concerned about the work ethic of those they refer (Smith & Young, 2017). Furthermore, women are less likely overall to provide job referral assistance, which could be attributed to larger patterns in labor market barriers and discrimination disproportionally affecting women (O'Connor, 2013; Zhou, 2019). In a study among Nicaraguan low-wage job seekers, contacts that perceived the seeker as untrustworthy or of low reputation would deny referrals, often deceptively saying there are no jobs or they can't make a referral, in order to maintain the relationship (Ibañez, 2021). Further, there are reasons to believe that a high level of social monitoring in an immigrant community would make reputational risk higher than in non-migration contexts (Coleman, 1988).

In addition, heterogeneity in status among immigrants may create cleavages in the immigrant community. In the case of Cubans in Miami, early-cohort wealthy migrants who arrived in the 1960s sought to distance themselves from newcomers that they perceived as lower status and thus provided limited access to resources for this group (Portes & Shafer, 2007). Based on these considerations, we propose the second hypothesis:

Hypothesis 2A (H2A): Immigrants are more likely to provide job search support or a referral to individuals who present a lower reputational risk.

Other work on the referral side shows that individuals will only tend to provide information to their strong ties, or to their weak ties whose job intentions are clear (Marin, 2012; O'Connor, 2013). Further, because immigrant co-ethnic or co-home country solidarity has been shown to lead to job support (Portes & Sensenbrenner, 1993), we propose the following hypothesis:

Hypothesis 2B (H2B): Co-ethnic or co-home country connection can moderate the effects of reputational risk on likelihood of job search support or a job referral

3.2.3 Immigrant Competition

Putnam distinguishes between two key types of capital that are particularly salient for migrants looking for work: "'bonding' social capital (ties to people who are like you in some important way) and 'bridging' social capital (ties to people who are unlike you in some important way)" (Putnam, 2007). Bridging ties to natives in the country of destination are seen as important for migrant labour market integration and social mobility. Bonding ties to country of origin's group are shown to be crucial to getting settled in a new area and finding one's first job upon migration (Lancee, 2012). Putnam argues that in the wake of increased flows of migration and diversity, trust and cooperation will decrease, even among individuals of the same group (2007). This can stem from different attitudes towards assimilation, "[a]mong immigrants, divergent views on integration versus cultural preservation contribute to declining intra-ethnic trust" (Williamson 2015, 1726). There is empirical evidence that intra-group connections foster competition for resources and distrust of migrants from the same origin (Ryan et al., 2008). In this context, migrants that feel there is a high level of competition are unlikely to help and support fellow migrants because it may affect their own labor market or wage outcomes (de Haas, 2010; Epstein, 2008). Feelings of distrust are amplified among undocumented immigrants who maintain smaller networks of co-ethnics because they fear being "caught" and thus need to balance trust and support for finding work (Bloch, 2013; Sigona, 2012). Furthermore, migrants or refugees might not want to engage in local co-ethnic networks for fear that information about their activities reaches back to individuals in their origin country, from whom they have fled (Arar, 2016; Williams, 2006). In such cases, connecting with immigrants of the same origin to provide support could put these refugees at risk (Williams, 2006).

In contexts of *high* competition for jobs, co-ethnic ties can be a liability, especially when there is a lack of trust among immigrants (Ryan et al., 2008; Williams, 2006). However, in cases where there is *low* competition for jobs, it is likely that immigrants present in-group bias instead of competition, and thus co-ethnic ties in this context would facilitate obtaining employment for immigrants (Aguilera, 2002, 2005; Aguilera & Massey, 2003; Greenwell et al., 1997). We thus propose the following hypothesis:

Hypothesis 3A: In non-competitive labor environments, immigrants will be more likely to offer support to individuals in their own migrant ethnic group than those in other groups, all else being equal. In competitive labor markets, immigrants will favor support for non-immigrants due to perceived competition.

In the case of a job shortage, other works have shown that social closeness can help overcome the difficulties associated with low-trust, highly competitive environments as seen among labour immigrants (Ryan et al., 2008), refugees (Williams, 2006), and undocumented immigrants (Bloch, 2013).

We therefore propose the following:

Hypothesis 3B: In competitive labor market environments, social closeness will trump ethnic solidarity among immigrants.

3.3 Data and Methods

3.3.1 Data

To test these hypotheses, we conduct an online survey on employment, migration history, history of providing job support and supporting their migrant community, and includes vignette experiments outlined below. This paper employs two different samples of Latin American immigrants. The first was collected using a platform that recruits survey takers from across the USA and the second was sample was recruited from the Raleigh-Durham area (RDU) of North Carolina. The sample from RDU allows us to study a new destination for Latin American immigrants, which attracts Latin American immigrants for both "white-collar" jobs like those pharma and tech, as well as "blue-collar" jobs like those in construction. Samples are described below.

3.3.1.1 Sample 1

Sample 1 survey participants were recruited through Lucid, a platform that allows respondents to be recruited from over 250 survey platforms. Experimental results from five different studies run on this platform have been shown to be comparable to experimental results from representative samples of the US population, among them the General Social Survey samples (Coppock & McClellan, 2019). In July and August of

2021, we recruited 550 adults (18+) who are currently located in the United States and born in a Latin American country or Puerto Rico. All participants have worked in the United States at some point (though they may be unemployed or in school now), all consented to take a 15 minute survey and passed two attention checks embedded in the survey. These checks involve very simple questions with obvious answers to ensure the participants are not merely clicking through the survey without reading the questions, which increases the quality of the survey responses (Buchanan & Scofield, 2018). Questionnaires were made available in English and Spanish. We did not include Portuguese surveys because Brazilians make up a small percentage of Latin American immigrants (2% per the 2019 ACS), and 57% of them report speaking English *Very Well,* and thus we do not deem we are excluding a substantial number of respondents from Brazil. We did receive 18 surveys from individuals born in Brazil, and they all took the survey in English. Of the 550 participants, 392 passed the randomization check, meaning they correctly answered questions about their vignette and experimental conditions, indicating they had sufficient comprehension of the vignette to participate in the experiment.

Table 10 shows descriptive statistics for the analytical sample 1. We show the median age of the sample is 30.2 years, two thirds are female, 97% identify as Hispanic and 46% are married. We find our sample skews female compared to the 2019 1-year weighted ACS estimates (US Census Bureau, 2019) for Latin American born (50.4%), skews younger (median of 44.9 years), and is more likely to identify as Hispanic (87%), and are less likely to be married (55.9%). The Lucid sample is also more educated than the ACS average for Latin-American-born in the USA. Only 7% of our sample does not have a high school degree, compared to 39.7% in the ACS, though a similar proportion have an Associates or some college (16% in our sample and 18% in the ACS). Our sample is more likely to have a Bachelors (31% compared to 10.2% in the ACS) and Graduate or Professional degree (14% compared to 5.1% in the ACS).

This sample is therefore not representative of the Latin American immigrant population in the United States, and the estimand for experimental analysis will be the Sampled Average Treatment Effect (SATE) (Coppock & McClellan, 2019). Results are likely generalizable to the population of Latin American born individuals who take online surveys and met the inclusion criteria. This is still an important sample because it can give us a "first look" at the relationship between reputation, competition, and job support among Latin American immigrants. All models control for sex, Hispanic identification, age, married and educational level. We also show that there is an underlying predisposition to offer job support in this sample. 63% of individuals have lent job support in the past, 29% have supported the job search of an individual from their home country, and on average each person in the sampled supported the search of 2.2 people. Among those who have ever helped another person, the main reasons for doing so were because they were qualified (32%), to help fellow immigrants (29%), and to help people (29%).

Table 10: Descriptive Statistics (Sample 1)

	Mean	Standard Deviation	N
Demographics			
Live in Urban Area	0.66	0.47	392
Median Age (years)	30.22	11.16	392
Female	0.66	0.47	392
Male	0.32	0.47	392
Other	0.02	0.13	392
Hispanic	0.97	0.18	392
Married	0.46	0.50	392
Educational Attainment			
No schooling	0.01	0.09	392
Elementary school	0.01	0.09	392
Middle School	0.05	0.22	392
Senior high	0.32	0.47	392
Associate degree	0.16	0.37	392
Bachelor’s degree	0.31	0.46	392
Master’s degree	0.11	0.32	392
Professional degree	0.03	0.16	392
Doctoral degree	0.01	0.11	392
Immigration			
Total years in USA	16.18	11.48	392
Came due to job	0.20	0.40	392
Work History			
Attending School	0.28	0.45	392
First Job in Private Sector	0.68	0.47	392
First Job Arranged	0.28	0.45	392
Got Help for First Job	0.52	0.50	392
Got Referral for First Job	0.30	0.46	392
Current Job in Private Sector	0.47	0.50	392
Got Help for Current Job	0.50	0.50	392
Got Referral for Current Job	0.17	0.38	392
Currently Employed	0.84	0.37	392

Support			
Have Given Job Search Help	0.63	0.48	392
Number of People Helped	2.23	7.68	392
Helped Person from Home country	0.29	0.45	392
Reason for Helping			
They were qualified	0.32	0.47	245
To help fellow immigrants	0.29	0.45	245
To help people	0.29	0.45	245
Felt badly for them	0.09	0.29	245
Felt pressure to help	0.00	0.06	245
Other	0.00	0.06	245
Community Altruism			
Emotionally obligated to home community	3.65	1.17	392
Feel strong sense of unity with the home community	4.13	1.01	392
Received support from the home community	3.53	1.36	392
Community needs support	3.89	1.14	392
Index (sum of 4 Community Vars)	15.19	3.63	392

Notes: All values are proportions or means, unless indicated otherwise. Median age is shown for comparability with American Community Survey data.

Table 11: Descriptive Statistics (Sample 2)

	Mean	Standard Deviation	N
Demographics			
Median Age (years)	33.33	6.73	107
Female	0.46	0.50	109
Male	0.54	0.50	109
Other	0.00	0.00	109
Hispanic	0.99	0.10	109
Married	0.76	0.43	109
Educational Attainment			
No schooling	0.03	0.16	109
Elementary school	0.01	0.10	109
Middle School	0.03	0.16	109
Senior high	0.11	0.31	109
Associate degree	0.11	0.31	109
Bachelor’s degree	0.40	0.49	109
Master’s degree	0.29	0.46	109

Professional degree	0.01	0.10	109
Doctoral degree	0.01	0.10	109
Immigration			
Total years in USA	8.41	6.50	109
Came due to job	0.52	0.50	109
Work History			
Attending School	0.06	0.23	109
First Job in Private Sector	0.90	0.30	109
First Job Arranged	0.50	0.50	109
Got Help for First Job	0.78	0.42	109
Got Referral for First Job	0.58	0.50	109
Current Job in Private Sector	0.74	0.44	109
Got Help for Current Job	0.80	0.40	109
Got Referral for Current Job	0.60	0.49	109
Currently Employed	0.89	0.31	109
Support			
Have Given Job Search Help	0.21	0.41	109
Number of People Helped	0.68	1.91	109
Helped Person from Home country	0.07	0.26	109
Reason for Helping			
They were qualified	0.13	0.34	23
To help fellow immigrants	0.26	0.45	23
To help people	0.52	0.51	23
Felt badly for them	0.09	0.29	23
Felt pressure to help	0.00	0.00	23
Other	0.00	0.00	23
Community Altruism			
Emotionally obligated to home community	3.39	1.01	109
Feel strong sense of unity with the home community	3.16	1.02	109
Received support from the home community	3.17	0.88	109
Community needs support	3.31	0.98	109
Index (sum of 4 Community Vars)	13.03	2.56	109

Notes: All values are proportions or means, unless indicated otherwise. Median age is shown for comparability with American Community

3.3.1.2 Sample 2

The second sample was recruited among Latin American Immigrants in the Raleigh-Durham area and was administered the same survey as Sample 1 (with Vignette 3 instead of Vignette 2, see Methods). This allows us to compare findings from Sample 1, Latin American immigrants from around the USA to findings for sample 2, Latin American immigrants from RDU, which includes higher education immigrants in "white-collar" jobs. With Sample 2, we also collect network data about a portion of the sample which can be used in future work on immigrant networks. In order to be eligible, respondents were required to be 18 or older, currently residing in Durham, Orange, or Wake counties in North Carolina and born in a Latin American country or Puerto Rico. The data collection protocol was reviewed by Institutional review board of Duke University.

Survey participants in Sample 2 were recruited via two means between January and April 2022. The first is through network sampling. The network sampling portion of the study was a hybrid of the Network Sampling with Memory (Mouw & Verdery, 2012) procedure used in Merli et al. (2022), in that it was researcher-guided and relied on nominations and referrals, and a snowball or chain referral sampling procedure (Biernacki & Waldorf, 1981) such as Respondent Driven Sampling, which typically relies on participants distributing coupons to their eligible contacts (Heckathorn, 1997, 2002). This portion of the recruiting proceeded as follows.

(1) 9 seed nodes were selected following qualitative interviews with members of the Latin American immigrant community in the Raleigh-Durham area. In this case, seeds were selected to represent different countries of origin within Latin America, as well as different genders and socioeconomic status.

(2) Surveys were sent via WhatsApp to these seeds. Participants received a gift card for their participation in the survey, with an additional gift card administered for referring at least 3 (and up to 6) eligible contacts in the Raleigh-Durham area in a separate survey.

(3) Of these seeds, 3 provided referrals to other members of the Latin American community. Each new referral was then contacted via WhatsApp to take the survey and give nominations and referrals.

(4) When referrals were given, all referred individuals were contacted to participate in the study. This diverges from sampling protocol in Network Sampling with Memory (NSM) (Merli et al., 2022; Mouw & Verdery, 2012), where the list of nominations forms a basis for a type of sampling frame, which is then sampled from using the NSM algorithm. Contacting all respondents is likely to lead to biased results, as immigrants who are connected to one another are likely to resemble each other in a number of ways (Gile et al., 2015; Gile & Handcock, 2010; Mouw & Verdery, 2012). This sampling approach is vulnerable to getting "stuck" in dense clusters of the network, which prevents the exploration of the network to obtain a more representative sample. However, due to the low rate of response (34.6% of contacted individuals), and the even lower proportion of individuals who have given referrals (20.0% of contacted individuals or 57% of those who took the survey), all referrals were contacted to take the survey to ensure as large a sample as possible.

(5) Respondents who did not answer the invitation to take the survey on WhatsApp were followed up with via WhatsApp (or another texting platform in a few cases where they did not have WhatsApp) four times after which they were considered "No Answer".

Figure 10 shows the network of respondents and referrals after 3 months of conducting the survey. The final sample size of completed surveys is 26.

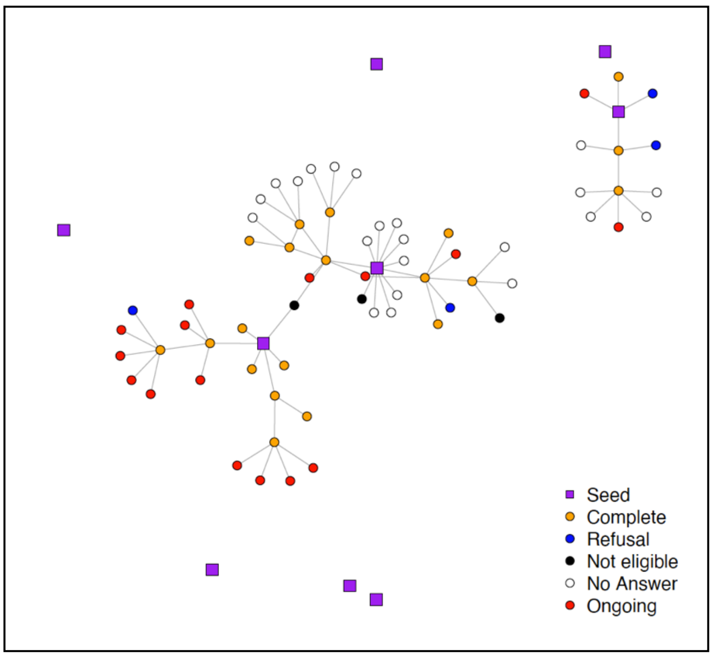

Figure 10: Network Graph of Sample 2 Network Sampling Respondents (75 Individuals)

In addition to the network sampling strategy, participants were recruited through Facebook groups for Latin Americans in the Raleigh-Durham Area through posting the survey in 3 different groups. Because we did not have direct contact information for these individuals and did not correspond with them directly, ensuring data quality of this sample was important. We removed any duplicate entries and verified that individuals spent at least 5 minutes taking the survey (around the time the quickest participants from the network sample spent) and completed the entire survey. After appending the data from both the network sample and the online sample, we removed all participants who did not pass either of the two embedded attention checks, which were the same as Sample 1 above. This left us with 88 participants from the online sample and 21 participants from the network sample, a total of 109.

Table 11 shows descriptive statistics for Sample 2. We compare this to the 2019 1-year weighted ACS estimates for the Raleigh-Cary Metro Area because this was the area most comparable to our sample with available tables for Latin American born from the US Census Bureau's data.census.gov (US Census Bureau, 2019). We show the median age of our Sample 2 is 33.3 years, 46% are female, 99% identify as Hispanic and 76% are married. We find our sample has a similar gender balance to the 2019 1-year weighted ACS estimates for Latin American born for the Raleigh-Cary Metro Area (48.3% female), skews younger (median of 42.3 years), and is more likely to identify as Hispanic (93%), and are more likely to be married (54.0%). Our sample is also more educated than the ACS average for Latin-American-born in the Raleigh-Cary Metro Area. Only 7% of our sample does not have a high school degree, compared to 42% in the ACS and a smaller proportion have an Associates or some college (11% in our sample and 16% in the ACS).

Our sample is more likely to have a Bachelors (40% compared to 9.6% in the ACS) and Graduate or Professional degree (31% compared to 6.4% in the ACS).

Similar to the Lucid sample, this population is not representative of the Latin American population according to the ACS for that area. This is not surprising given the methods used to reach participants were WhatsApp and Facebook, and younger, more educated individuals may be both more likely to be online and more likely to take the survey once contacted. All models control for sex, Hispanic identification, age, married, educational level and whether the sample was collected via network or online.

A marked difference from Sample 1 is the lower proportion of individuals from Sample 2 who have ever provided job help. 21% of individuals have lent job support to another person, compared to 63% for Sample 1. Just 7% have supported the job search of an individual from their home country, and on average each person in the sampled supported the search of 0.68 people. Among those who have ever helped another person, the main reasons for doing so were because they were qualified (13%), to help fellow immigrants (26%), and to help people (52%). Indeed, this group appears to focus less on supporting their own immigrant group than helping people in general than the Lucid sample (Sample 1). They show less overall unity to their immigrant community with a Community Index of 13.03 compared to 15.19 in Sample 1. This is calculated using a series of 4 questions on a 5 point Likert scale and displayed in Table 11: (1) I feel emotionally obligated to the community from [home country] in North Carolina (2) I feel a very strong sense of unity with the [home country] community (3) I have received support (both material and non-material) from the [home country] community that have been very important to me (4) The global pandemic has greatly affected the [home country] community in North Carolina, which now has a great need for support and resources from its members.

3.3.2 Methods

3.3.2.1 Factorial Survey

To better understand the underlying factors that contribute to the decision about whether to refer a fellow migrant for a job, we use a factorial survey, consisting of two hypothetical scenarios that we express with vignettes. Factorial studies enable the estimation of attitudes and motivations, particularly when the subject matter is sensitive and can reveal latent decision-making processes which people may not be aware of when making a choice (Auspurg et al., 2014). They can also be applied in a "real life" setting beyond the lab, among participants who have faced these decisions themselves (Aguinis & Bradley, 2014). The vignettes in this study mimic real-life scenarios that could be encountered by migrants when they are faced with the decision of helping (or not helping) others with their job search. In our study's case, hypothetical scenarios present a distinct advantage in presenting situations that impose exogeneity of immigrant connections, reputational risk, job shortage context, and strength of tie. Immigrants are often connected to other immigrants from their hometowns or countries, and are likely to surround themselves with people who have similar character traits, including reputation (see McPherson, Smith-Lovin, and Cook 2001; Mouw 2003). This implies that a purely observational study would be vulnerable to bias in part because people select both their friends *and* the people they refer for jobs. Those who approach friends for job referrals may also be selected on characteristics like reputation and status. Using a third person vignette allows us to abstract from the problems that occur when this sort of network homophily is not controlled (Mouw, 2003, 2006). In using vignette experiments to study the link between immigrant characteristics and likelihood of a job referral, we ensure that respondents in the treatment and control groups are balanced on observable and unobservable characteristics. Still, social desirability bias (SDB) may be a concern if either the treatment or control condition leads respondents to disproportionately want to exhibit social desirability (Larson, 2019). To verify that this is not affecting the results, we run models that control for an "altruism index", an index made of four questions on altruism and redistribution, which are likely to be subject to social desirability and are answered before the respondent sees the vignette, which seeks to capture baseline levels of SDB. We do not find this affects the results.

3.3.2.2 Vignettes

The risk vignette (Vignette 1) was identical in both Sample 1 and 2. The competition vignette was changed such that Sample 1 was administered only Vignette 2 and Sample 2 was administered only Vignette 3. In Vignette 3, we alter the job market conditions such that one condition shows a job shortage (details below). This was a more appropriate experiment for Sample 2, the RDU area, where there are more "white-collar" and higher education workers who may be more sensitive to competition for jobs. We present the risk vignette and the competition vignette in random order to study participants. After each vignette, we ask three questions which check comprehension of the two randomized conditions and of a third characteristic of the vignette.

Vignette 1

José is an immigrant from [respondent's home country], currently living in [respondent's current state]. He works in a firm where there are many employees from Latin America. He is a fairly new employee and is working hard to impress his boss. He receives the resumé of David, <u>a contact from his hometown in [respondent's home country]</u>. When he asks around about David, he finds out that <u>he was previously fired for not showing up to work</u>

	Factor	Level	Vignette Text
1	Immigrant connection	High	a contact from their hometown in [home country]. He sees on his resumé that they went to the same primary school back home
		Medium	a contact from the Latino immigrant community center in [current state]
		Low	a non-Latino American contact who was born and raised in [current state]
2	Reputational risk of contact	Low(er) risk	he has very little work experience in this type of work, and most of his experience has been in construction
		High risk	he was previously fired for not showing up to work

Questions

Please indicate to what extent you agree with the following statements:

1. José should help David by sharing information about his own experience in the [current state] labour market
2. José should explain to David where to send his resumé
3. José should help David with his resumé and cover letter
4. José should recommend David to his boss for a job

Vignette 2

> Juan is a recent immigrant from [respondent's home country] in [respondent's current state]. There is currently a job shortage in [respondent's current state], creating a difficult environment for finding a job. A close friend, Daniel, with whom Juan spends a lot of time, approaches him to ask if he has any information about local jobs. Daniel is a contact from their hometown in [respondent's home country] who grew up a few blocks from Juan. Juan knows about a good job opening in a local firm that employs many from [respondent's home country] but he is unemployed himself and is thinking of applying for the job.

	Factor	**Level**	**Vignette Text**
1	Strength of tie	High	A close friend, Daniel, with whom Juan spends a lot of time
		Low	A person Juan has heard of, but never met directly himself, Daniel,
2	Immigrant connection	High	a contact from their hometown in [home country who grew up a few blocks from Juan
		Medium	a contact from the Latino community center in [current state]
		Low	a non-Latino American contact who was born and raised in [current state]

Questions

Please indicate to what extent you agree with the following statements:

1. should help Daniel by sharing information about his own experience in the [current state] labor market
2. Juan should help Daniel with his resumé and cover letter
3. Juan should recommend and encourage Daniel to apply for that job
4. Juan should explain to Daniel how to apply to this job, including where to send his resumé

Vignette 3

Juan is a recent immigrant from [respondent's home country] in the Raleigh-Durham area. There is a job shortage in the Raleigh-Durham area, creating a difficult environment for finding a job. A contact, Daniel, approaches him to ask if he has any information about local jobs. Daniel is a contact from their hometown in [home country] who grew up a few blocks from Juan. Juan knows about a good job opening in a local firm that employs many from [home country] but he is unemployed himself and is thinking of applying for the job.

	Factor	**Level**	**Vignette Text**
1	Job Shortage	High	is a job shortage in the Raleigh-Durham area, creating a difficult environment for finding a job
		Low	are a lot of jobs available in the Raleigh-Durham area, meaning it is easy to find a job
2	Immigrant connection	High	a contact from their hometown in [home country who grew up a few blocks from Juan
		Medium	a contact from the Latino community center in [current state]
		Low	a non-Latino American contact who was born and raised in [current state]

Questions

Please indicate to what extent you agree with the following statements:

1. should help Daniel by sharing information about his own experience in the [current state] labor market
2. Juan should help Daniel with his resumé and cover letter
3. Juan should recommend and encourage Daniel to apply for that job
4. Juan should explain to Daniel how to apply to this job, including where to send his resumé

For each vignette, we ask how much respondents agree with a series of statements about desire to provide job search help, to be answered on a Likert Scale (1 = Strongly Disagree 7= Strongly Agree). This is a scale that allows one to capture variation in desire to help and is used in similar vignette studies (Glock & Schuchart, 2019; Yokota & Nakanishi, 2017). Gauging agreement with a series of statements about desire to help will allow us to evaluate what *types* of help respondents would be willing to provide, and how this differs across manipulations of the vignette.

Our vignettes each have 2 factors, one with 3 levels and one with 2, yielding 6 possible variations of each vignette, with each vignette equally likely to be selected. Tables 12 and 13 show the breakdown of respondents randomly assigned to each of the six cells, with a total of 392 for Sample 1 and 109 for Sample 2. Table 14 and Table 15 show the means of the 8 dependent variables across all random conditions for Sample 1 and Sample 2. We find that respondents from Sample 1 to Vignette 1, on average, agree with recommending David to José's boss at a level of 4.53 points out of 7 (lowest agreement question), but agree that José should explain to David where to send his resumé at a level of 5.65 points out of 7 (highest agreement question). For Sample 2, in Vignette 1, we find respondents agree with giving a job recommendation at a level of 4.50 out of 7 (lowest agreement question) and agree that José should help David by sharing information about his own experience at a level of 5.04 (highest agreement question).

For the second vignette, average responses range from 5.39 for *Juan should help Daniel with his resumé and cover letter*, to 5.92 for *Juan should help Daniel by sharing information about his own experience in the [local] labor market*.

For the third vignette, we find the lowest agreement question is that Juan should help Daniel by sharing information about his own experience in the Raleigh-Durham labor market (score of 4.60) and the highest is Juan should help Daniel with his resumé and cover letter (5.02). The *Total* rows in Table 14 and 15 are the sum of all four dependent variable scores for each vignette. we sum them and call them "Support Index".

The Appendix C Table 21 and Table 22 show the results of a Balance check among key variables for one of the random variables for each vignette (Risk level for Vignette 1, Tie Strength for Vignette 2, and Job Shortage for Vignette 3). All variables are balanced across experimental conditions with the exception of educational attainment. This is not of great concern as we control for education in all models.

Table 12: Number of Observations in Each Condition (Sample 1)

		Risk		**Tie Strength**	
		Low	High	Low	High
Connection	Low	57	71	59	69
	Medium	76	57	76	57
	High	63	68	55	76
	Total count	196	196	190	202

Table 13: Number of Observations in Each Condition (Sample 2)

		Risk		Job Shortage	
		Low	High	Low	High
Connection	Low	19	17	14	18
	Medium	16	19	15	22
	High	24	14	17	23
	Total count	59	50	46	63

Table 14: Dependent Variable Descriptive Statistics (Sample 1)

	Vignette 1 (Risk)			
	Mean	SD	[Min,Max]	N
José should help David by sharing information about his own experience in the [local] labor market	5.54	1.41	[1,7]	392
José should explain to David where to send his resumé	5.65	1.28	[1,7]	392
José should help David with his resumé and cover letter	5.17	1.58	[1,7]	392
José should recommend David to his boss for a job	4.53	1.76	[1,7]	392
Total	20.89	5.04	[4,28]	392
	Vignette 2 (Competition)			
	Mean	SD	[Min,Max]	N
Juan should help Daniel by sharing information about his own experience in the [local] labor market	5.92	1.13	[1,7]	392
Juan should help Daniel with his resumé and cover letter	5.39	1.36	[1,7]	392
Juan should recommend and encourage Daniel to apply for that job	5.60	1.35	[1,7]	392
Juan should explain to Daniel how to apply to this job, including where to send his resumé	5.65	1.33	[1,7]	392
Total	22.56	4.49	[4,28]	392

Notes: All values are proportions or means, unless indicated otherwise.

Table 15: Dependent Variable Descriptive Statistics (Sample 2)

	Vignette 1 (Risk)			
	Mean	SD	[Min,Max]	N
José should help David by sharing information about his own experience in the Raleigh-Durham labor market	5.06	1.63	[1,7]	109
José should explain to David where to send his resumé	4.96	1.64	[1,7]	109
José should help David with his resumé and cover letter	4.85	1.67	[1,7]	109
José should recommend David to his boss for a job	4.50	1.63	[1,7]	109
Total	19.38	4.53	[4,28]	109
	Vignette 3 (Competition)			
	Mean	SD	[Min,Max]	N
Juan should help Daniel by sharing information about his own experience in the Raleigh-Durham labor market	5.02	1.78	[1,7]	109
Juan should help Daniel with his resumé and cover letter	4.60	1.69	[1,7]	109
Juan should recommend and encourage Daniel to apply for that job	4.90	1.62	[1,7]	109
Juan should explain to Daniel how to apply to this job, including where to send his resumé	4.96	1.58	[1,7]	109
Total	19.48	4.97	[4,28]	109

Notes: All values are proportions or means, unless indicated otherwise.

3.3.2.3 Analytical Strategy

Outcome models for each vignette (competition and reputation) are estimated separately and each outcome measure is modeled separately. The most basic equation that we estimate is as follows, with coefficients presented in table on the right. This is expressed for Vignette 1 (Reputation):

$$Y_i = \alpha_0 + \gamma \text{Rep}_{Hi} + \delta \text{Imm}_{Hi} + \theta \text{Imm}_{M\,i} + \eta \text{Rep}_{H\,i}\text{Imm}_{H\,i} + \zeta \text{Rep}_{H\,i}\text{Imm}_{M\,i} + X_i{}'\beta_1 + \varepsilon_i$$

Where Yi is the outcome measure for the model (Likert scale for different statements about desire to help) for respondent i. The reference category is being assigned to Low on both factors. γ denotes the main effect of Factor 1, where Rep_{Hi} is the indicator that respondent *i* is assigned to the High level of that factor, indicated by the subscripted letter (High=H, Low=L). Similarly for Factor 2. η and ζ allow us to evaluate the interaction between Factor 1 and Factor 2. X_i is a vector of respondent covariates.

The equation for the reputational risk vignette will allow us to evaluate Hypothesis 2B, co-ethnic or co-home country connection can moderate the effects of reputational risk on likelihood of job search support or a job referral. If this is true, we expect $\gamma < 0$ (higher reputational risk associated with lower values on the Likert Scale for each job search help statement). We also expect Latino immigrants to be more likely to recommend help for other Latin American immigrants in situations of high reputational risk, compared to local non-Latin Americans ($\delta + \eta > \zeta + \theta > 0$). We expect a stronger effect on the likelihood of referring another individual from same hometown.

For the competition vignette, we estimate the same equation with the factors and levels from the reputation vignette. This allows us to test Hypothesis 3A, that in non-competitive labor environments, immigrants will be more likely to offer support to individuals in their own migrant ethnic group than those in other groups, all else being equal and that the opposite will be true in a job shortage. Therefore, we expect, when $\gamma > 0$ (positive coefficient on job shortage), then ($\delta + \eta < \zeta + \theta < 0$), such that individuals will be less likely to offer job support to immigrants in their own group than those in other groups. We will use the same model to test Hypothesis 3B, that in competitive labor market environments, social closeness will trump ethnic solidarity among immigrants. If this is true, we expect $\gamma > 0$ because stronger ties are likely to matter more in the presence of competition. We also expect there not to be an interaction between the two factors, because immigrant connection will not be a salient factor in decision making in competition contexts.

3.4 Results Sample 1

3.4.1 Job Support Is More Likely Among Co-ethnic Immigrants

Results show strong evidence for H1, that individuals are more likely to provide job search support to individuals in their own migrant group than those in other groups. Figure 11 shows predicted values from regressions above. We find that for Vignette 1, José and David having no immigrant connection, i.e., David being neither from the Latino Community Center nor from the respondent's home country, is associated with a significantly lower likelihood of the respondent proposing job support of any kind.

Sample 1

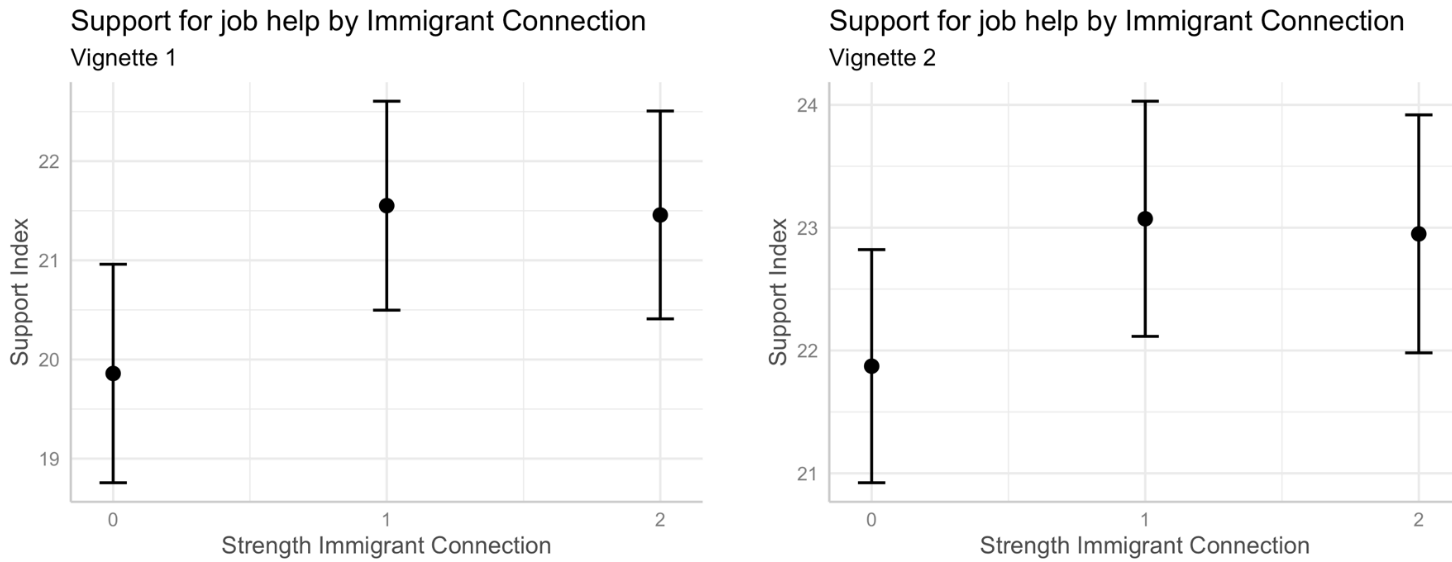

Figure 11: Relationship Between Immigrant Connection and Job Support Index for Each Vignette (Sample 1)

Note: Figures show results of predicted values from regressions that control for sex, age, married, Hispanic identification and education. The left figure pools results across risk levels and the Y-axis shows the Support Index for Vignette 1, which is on a scale of 4-28. The right figure pools results across Tie strength and the Y-axis shows the Support Index for Vignette 2, which is also on a scale of 4-28.

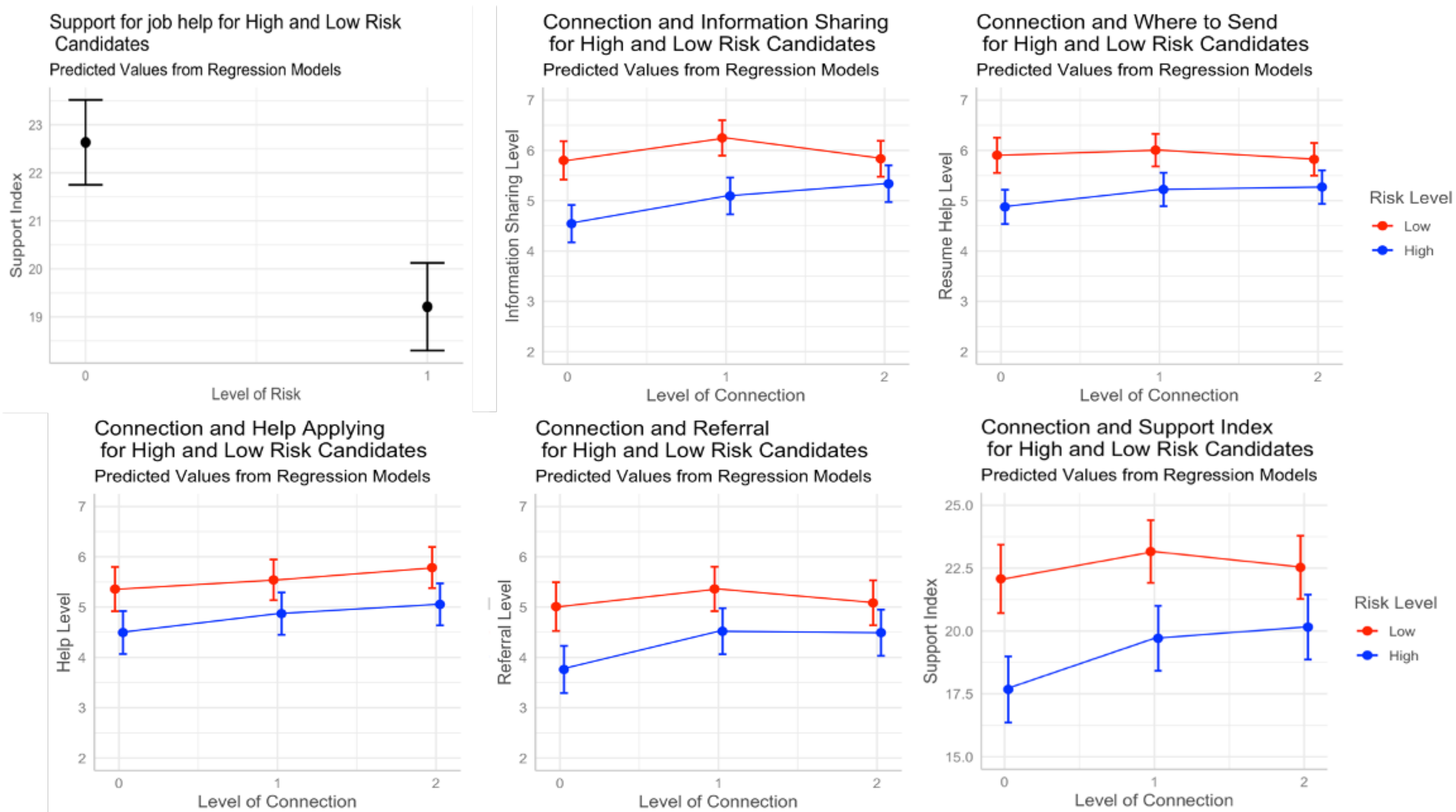

Figure 12: Experimental Results from Vignette 1 (Sample 1)

Notes: All values are predicted values from regression with demographic controls. Top left pools all levels of immigrant connection. Top middle shows outcome of *José should help David by sharing information about his own experience in the [local] labor market* on a Likert Scale from 1-7. Top right shows outcome of *José should explain to David where to send his resumé* on a Likert Scale from 1-7. Bottom left shows outcome of *José should help David with his resumé and cover letter* on a Likert Scale from 1-7. Bottom middle shows outcome of *José should recommend David to his boss for a job* on a Likert Scale from 1-7. Bottom right shows total support index.

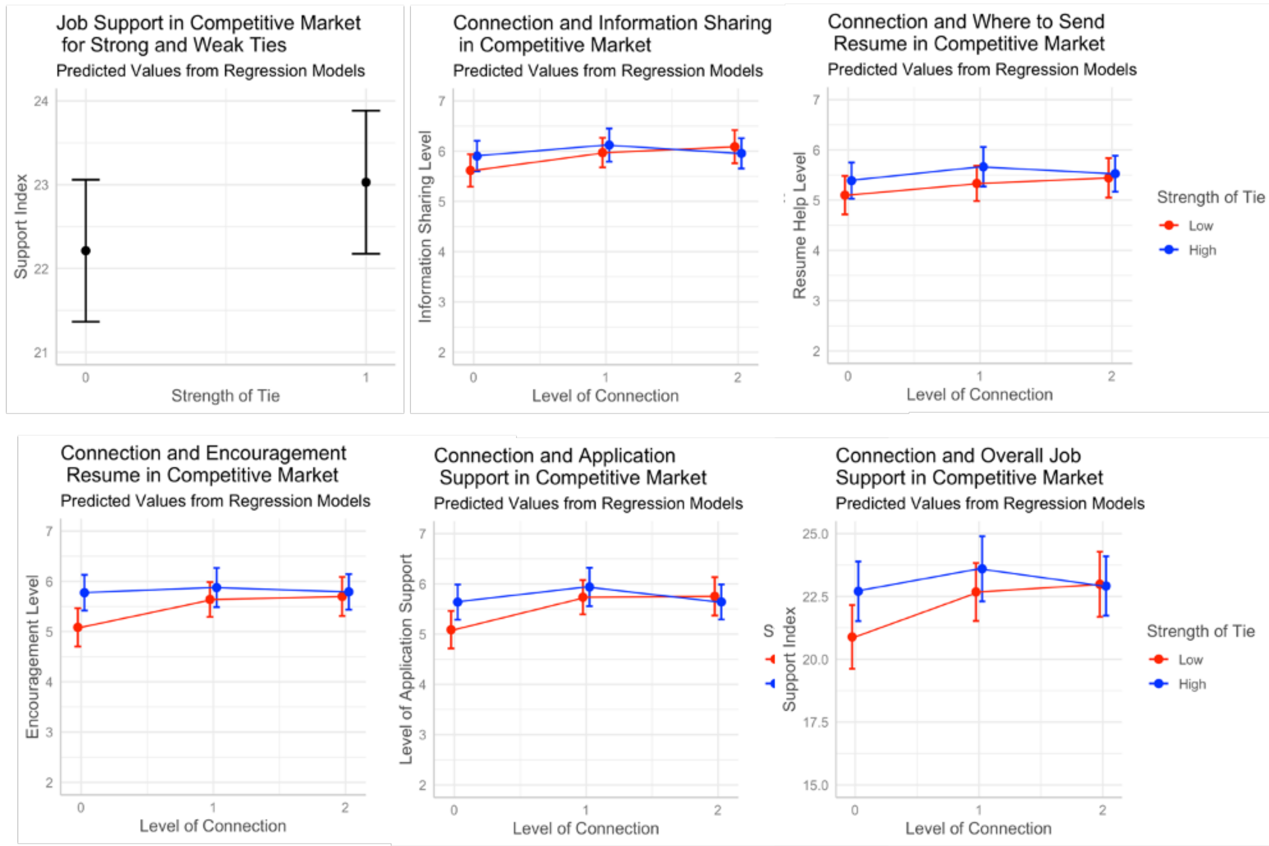

Figure 13: Experimental Results from Vignette 2 (Sample 1)

Notes: All values are predicted values from regression with demographic controls. Top left pools all levels of immigrant connection. Top middle shows outcome of *Juan should help Daniel by sharing information about his own experience in the [local] labor marke*t on a Likert Scale from 1-7. Top right shows outcome of *Juan should help Daniel with his resumé and cover letter* on a Likert Scale from 1-7. Bottom left shows outcome of *Juan should recommend and encourage Daniel to apply for that job* on a Likert Scale from 1-7. Bottom middle shows outcome of *Juan should explain to Daniel how to apply to this job, including where to send his resumé* on a Likert Scale from 1-7. Bottom right shows total support index.

Indeed, the overall predicted values for providing support for a non-Latin American are 1.69 points lower than for those who are members of the Latino community centre ($p<0.01$) and 1.60 points lower than those from the respondent's home country ($p<0.05$), on a scale of 0-28. We find a similar trend for the competition scenario vignette. Predicted values for providing support for a non-Latin American when there are few jobs available are 1.2 lower than those who are members of the Latino community centre ($p<0.05$) and 1.08 lower than those from the respondent's home country ($p<0.1$).

This is unsurprising in light of the rich literature on co-ethnic hiring and inter-immigrant support (Jiobu, 1988; Portes, 1998; Portes & Jensen, 1989; Portes & Shafer, 2007; Wilson & Portes, 1980). For example, Damm (2009) finds that living in an enclave is associated with increased wages, which she attributes in part to information about jobs being transmitted through the ethnic network leading to better job matches. Bailey and Waldinger (1991) argue that co-ethnic hiring is more effective because being from the same immigrant community means the employee behavior is more predictable and thus it is easier to foster trust between the existing company and the new employee. Our findings support this conclusion and lend another dimension to existing work, namely that referrals and direct support with cover letters and resumes are additional factors that may support better matches in an enclave economy.

There is no significant difference in likelihood of support between candidates from the Latino community center and those from the individual's hometown. This is in line with previous findings that the effects of in-group identity on supportive behaviour eclipses the effects of social proximity (Baldassarri & Grossman, 2013). This also is partially congruent with the notion that larger market societies promote more fairness than smaller, kin-based societies, which may explain why there is no distinct "hometown" advantage (Henrich et al., 2010).

3.4.2 "Riskier" Candidates Less Likely to Receive Job Application Support

Figure 12, in the top left, "Support for Job Help for High and Low Risk Candidates", shows predicted values of likelihood of job search support, for candidates that were in the Low versus High risk categories. Findings support H2A, that immigrants are more likely to provide job search support or a referral to individuals who present a lower reputational risk. On average, across all connection conditions, candidates who are deemed riskier because they had been fired in the past have a job support index 3.4 points lower, on a scale of 1-28, than candidates who are less risky as they are merely inexperienced ($p<0.001$). The other graphs in Figure 12 reveal similar trends across each level of immigrant connection.

Previous work in this area shows that individuals heavily weight their own reputational risk and likelihood that the job seeker will do a "good job" when deciding whether or not to give a job referral (O'Connor, 2013; Smith, 2005, 2007, 2010; Smith &

Young, 2017), particularly for minorities. Indeed, those providing job support or a referral are mindful of the job seeker's reputation, even when they are family (Ibañez, 2021). This finding also echoes work that unemployed workers are less likely to get a referral due to the reputational risk this poses the referrer (Bond & Fernandez, 2019). Furthermore, the respondent may be considering risks to their *own* reputation when choosing whether or not to help a risky candidate (Coleman, 1988; Smith, 2005, 2010). Indeed, in networks with social closure, the case of many immigrant networks (Lubbers et al., 2007, 2010), individuals will be more mindful of their reputation because the network can more easily impose sanctions for undesirable behavior (Coleman, 1988).

3.4.3 Co-ethnic Ties Moderate the Effect of Risk for Job Candidates

The graphs in Figure 12 lend support for H2B, co-ethnic or co-home country connections can moderate the effects of reputational risk on likelihood of job search support or a job referral. Graphs each show the link between immigrant connection (non-Latino=0, co-ethnic=1, or home-country=2), and different forms of help recommended that José provide to David. The top middle graph shows results from the question "José should help David by sharing information about his own experience in the [local] labour market" with responses on a scale of 1 (Strongly Disagree) to 7 (Strongly Agree). We show that, while the higher risk candidates receive lower points on this scale overall, the gap closes as the relationship between José and David changes. When David is presented as a non-Latin American, the gap in the scale between high and low risk is 1.26 (p<0.001). When he is presented as a member of the Latino Community Center, the gap is 1.154 (p<0.001). Lastly, when he is presented as a hometown contact, the gap is only 0.5 (p<0.03). Therefore, while the gap does not close completely, we do see evidence of immigrant connection moderating the relationship between riskiness and information sharing. We see similar results across all other outcome variables in Figure 12, where the gap closes as the immigrant connection becomes stronger.

Respondents may perceive that these forms of job support are even *more* important for immigrants from José's hometown, because they may be lacking even basic understanding of local job dynamics. This can outweigh the concern of reputational risk. This may be seen as a low-cost way to maintain the relationship between José and David, which can be important in close-knit communities (Gowan, 2011; Ibañez, 2021).

The bottom right graph in Figure 12 summarizes the results for all four dependent variables in an index on a scale form 0 to 28. Again, higher risk candidates receive lower points on this scale, but the gap narrows as the relationship between José and David changes. When David is presented as a non-Latino American, the gap in the scale between high and low risk is 4.40 (p<0.001). When he is presented as a member of the Latino Community Center, the gap is 3.45 (p<0.001). Lastly, when he is presented as a hometown contact, the gap is only 2.37 (p<0.01).

These results align with expectations about co-ethnic ties mitigating some risk factor. There are two key reasons we may see this result. Firstly, ethnic solidarity is particularly important in immigrant communities because it is often fundamental to getting settled in a new country (Portes & Manning, 1986) which explains why the same result may not occur in non-immigrant minority communities (Gowan, 2011; Smith, 2005, 2007). Secondly, immigrant communities by virtue of being formed through networks (Merli et al., 2022) are close-knit and thus subject to social monitoring (Coleman, 1988). In these contexts, not helping a fellow migrant in need (e.g. someone with difficulty finding work), may result in social sanctioning (Portes, 1998).

3.4.4 Stronger Ties Predict Higher Levels of Job Support for Candidates in a Competitive Environment

The top left graph in Figure 13 shows partial support for H3B, that in competitive labor market environments, social closeness will trump ethnic solidarity among immigrants. When Juan and Daniel are close friends, compared to being strangers, respondents are more likely to recommend job support by 0.82 points on the 28 point scale, though this is only significant at the 0.1 level.

Indeed, existing literature on job referrals considers tie strength as an important factor in predicting job support. Individuals will feel more obliged to help strong ties due to social reciprocity norms (Smith 2007; Newman 1999), and closer friends or family will also have a better sense of what sorts of jobs their tie could apply to and which openings they may be interested in (Marin, 2012). Further, people are significantly more likely to give a referral to an unemployed friend than a stranger, and more likely to do so non-anonymously, which can help seekers overcome this stigma and land a job (Bond & Fernandez, 2019).

3.4.5 Social Closeness Will Trump Ethnic Solidarity in a Competitive Environment

Graphs in Figure 13 provide partial support for H3B, that social closeness will trump ethnic solidarity in a competitive environment. Each figure shows the link between immigrant connection (non-Latino=0, co-ethnic=1, or home-country=2), and a different form of help that respondents recommend Juan provide to Daniel. In these figures, we expect the predicted values trend to be flat, such that connection does not play an important role, but that Strength of Tie on the y-axis is the defining factor for whether Juan should provide Daniel support in a competitive environment, which would give two parallel lines, with higher tie strength on top. The hypothesis is only partially supported. While the graph in the top middle, “Juan should help Daniel by sharing information about his own experience in the local labour market”, and top right, “Juan should help Daniel with his resumé and cover letter” show flat trends across connection levels, this is not the case for other dependent variables.

In the graphs in the bottom row, we find positive and significant interaction effects for the relationship between *tie*connection* and *Encourage to Apply*, and *Help with How to Apply*, respectively. This indicates that in a competitive environment, there is a positive, additive effect of being co-ethnic and having a strong friendship tie on respondents recommending job support. Indeed, in these graphs, the effect of strength of tie is strongest for low levels of immigrant connection (non-Latino), compared to co-ethnic connections or hometown connections. This indicates that strength of tie predicts job referral only for *low* immigrant connections but not medium (Latino community center) and high (hometown) immigrant connection.

This differential effect runs counter to existing work on immigrant competition. Previous qualitative work finds that competitive environments would foster lower job support among immigrants that have co-ethnic or co-home-town connections (Ryan et al., 2008). Work at the intersection of social capital and cohesion has found that ethnic diversity can lead to mis-trust, which may dampen pro-social behaviour (Portes & Vickstrom, 2011; Putnam, 2007; Williamson, 2015). In this case, it would mean that individuals should be just as, or less likely to refer a fellow immigrant than, say, a native-born American in a situation where there are few jobs available. However, this does not appear to be the case.

Instead, findings better align with experimental work on job referrals in non-immigrant contexts. In another experimental study, individuals were *more* likely to help out a job seeker in a competitive job environment, presumably because they understood the difficulty they were experiencing (Bond & Fernandez, 2019).

Interestingly, in Figure 13 graphs in the top middle, bottom middle and bottom left, we see a slight reversal of the trend for immigrant connection from Juan's home-country (connection=2). When both individuals are from the same hometown, respondents are *just as* likely, or even *less* likely, to recommend job support regardless of a strong or weak tie, whereas that gap is much larger for non-co-ethnic ties. This speaks to the importance of hometown connection for deciding whether or not to lend support, as it can help overcome a deficiency in tie strength. Indeed, new arrivals from an immigrants' hometown often rely on this hometown connection to get settled at destination, even when their ties at destination are not yet formed or strong (Aguilera, 2002, 2005; Garip & Asad, 2016; Massey, 1986, 2004; Massey & Espinosa, 1997). This finding showcases an important mechanism of this dimension: namely that immigrants can rely on others from their hometown, even when the labor market situation is unfavorable.

Sample 2

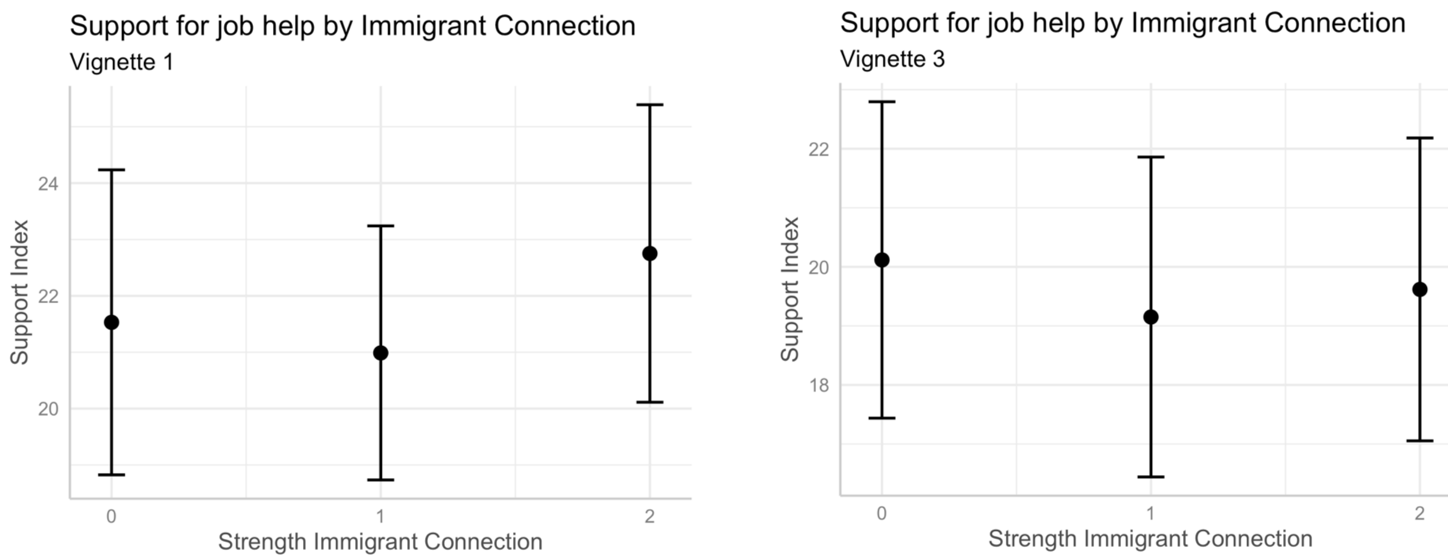

Figure 14: Relationship Between Immigrant Connection and Job Support Index for Vignettes 1, 3 (Sample 2)

Note: Figures show results of predicted values from regressions that control for sex, age, married, Hispanic identification and education and an indicator for whether respondent was found through network sampling or Facebook group. Left figure pools results across risk levels and the Y-axis shows the Support Index for Vignette 1, which is on a scale of 4-28. Right figure pools results across Tie strength and the Y-axis shows the Support Index for Vignette 3, which is also on a scale of 4-28.

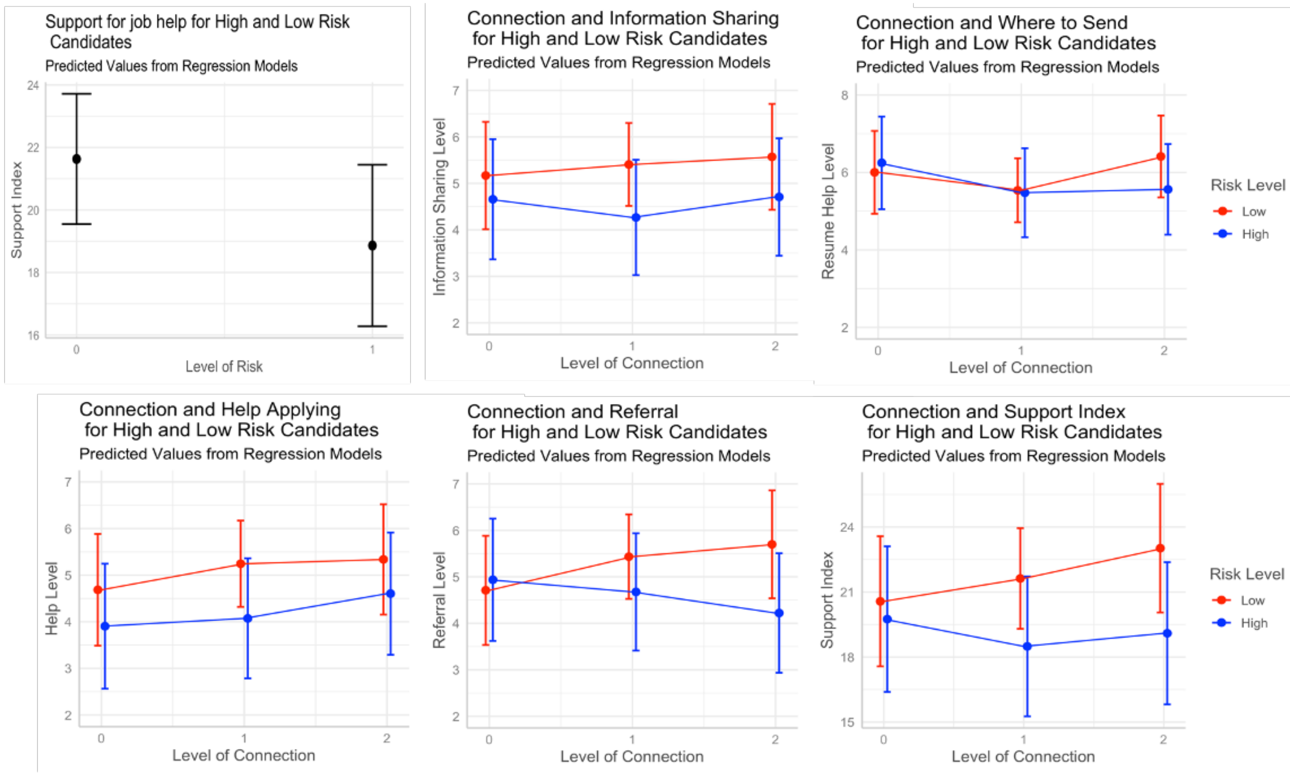

Figure 15: Experimental Results from Vignette 1 (Sample 2)

Notes: All values are predicted values from regression with demographic controls. Top left pools all levels of immigrant connection. Top middle shows outcome of *José should help David by sharing information about his own experience* on a Likert Scale from 1-7. Top right shows outcome of *José should explain to David where to send his resumé* on a Likert Scale from 1-7. Bottom left shows outcome of *José should help David with his resumé and cover letter* on a Likert Scale from 1-7. Bottom middle shows outcome of *José should recommend David to his boss for a job* on a Likert Scale from 1-7. Bottom right shows total support index.

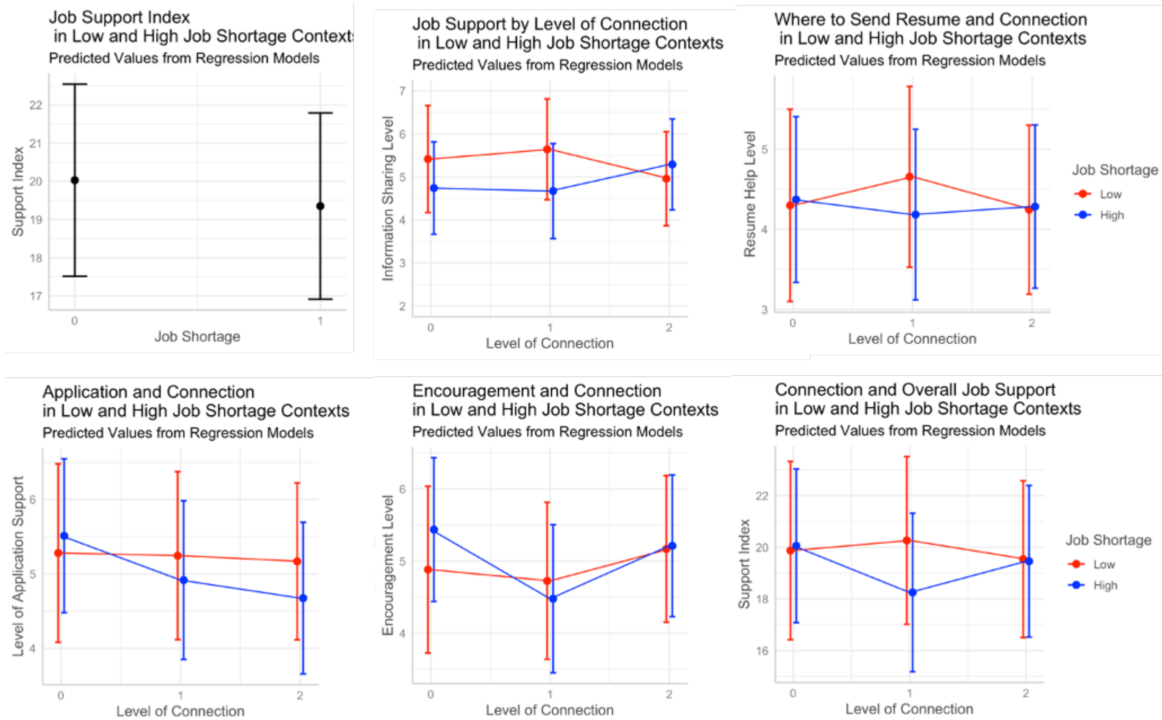

Figure 16: Experimental Results from Vignette 3 (Sample 2)

Notes: All values are predicted values from regression with demographic controls. Top left pools all levels of immigrant connection. Top middle shows outcome of *Juan should help Daniel by sharing information about his own experience in the [local] labor market* on a Likert Scale from 1-7. Top right shows outcome of *Juan should help Daniel with his resumé and cover letter* on a Likert Scale from 1-7. Bottom left shows outcome of *Juan should explain to Daniel how to apply to this job, including where to send his resumé* on a Likert Scale from 1-7. Bottom middle shows outcome of *Juan should recommend and encourage Daniel to apply for that job* on a Likert Scale from 1-7. Bottom right shows total support index.

3.5 Results Sample 2

Sample 2 results are "weaker", in that there are fewer models that show statistically significant differences between groups. For example, there is no statistical difference in job support among different immigrant connection levels in Figure 14. This is due, in part, to the smaller sample size. In this section, we discuss some of the key findings from this Sample and how they relate to Sample 1 results.

3.5.1 Co-ethnic Ties Exacerbate the Effect of Risk for Job Candidates

The top left graph in Figure 15 shows, as in Sample 1, that higher risk candidates, on average, receive lower levels of recommended job support, aligning with Hypothesis 2A. However, the moderating effect of immigrant home country connection appears to be absent for this sample. In the bottom right graph, overall support index, we see that while there is no gap or a low gap (not statistically significant) in the job support index between high and low risk candidates when the candidate is a non-Latin American, when the candidate is from the Latino community centre (connection=1), the gap is 3.13 ($p<0.1$), is, and when the candidate is from the same hometown (connection =2), the gap is 3.926 ($p<0.01$) on a scale of 4 to 28. This result is surprising in that it runs counter to findings in Sample 1, and to Hypothesis 2B. However, given what we know about immigrant networks and reputation, it is not all surprising. Respondents may feel that providing a recommendation or support to a risky candidate from their own community will poorly affect their own reputation. It is possible that the lower levels of intracommunity altruism among respondents in Sample 2 shown in the data section mean individuals both do not feel socially obligated to their community, but also are less concerned about social sanctioning from not helping other community members with a job referral (Coleman, 1988). It is worth noting that this finding is most apparent the bottom middle graph of Figure 15: *José should recommend David to his boss for a job*. Indeed, this is where we would expect reputation to matter the most (Smith, 2005), providing additional support for the idea that respondents in the Raleigh-Durham area are less concerned with social sanctioning and more concerned with reputation, in this context. This is likely exacerbated by the fact that the RDU has more individuals on average in high-skilled employment, which would make them more sensitive to this sort of risk.

Further, the gap between high and low risk candidates with a hometown connection (connection = 2) in the bottom middle and bottom right graphs of Figure 15 is largely driven by higher likelihood of recommending José give a job a referral when David is a low risk candidate and has a hometown connection than when he is a low risk candidate who is non-Latin American. Indeed, this shows evidence of strong co-ethnic support overall, in line with H1, but high resistance to risky candidates, regardless of origin or ethnic background.

3.5.2 In a Job Shortage, Individuals Are Less Likely to Refer Some Individuals From Same Migrant Group

Results from Vignette 3 allow us to test H3A, that in non-competitive labor environments, immigrants will be more likely to offer support to individuals in their own migrant ethnic group than those in other groups, all else being equal. In competitive labor markets, immigrants will favor support for non-immigrants due to perceived competition. Graphs in Figure 16 show the link between immigrant connection (non-Latino=0, co-ethnic=1, or home-country=2), and a different form of help that respondents recommend Juan provide to Daniel. None of the results from this vignette experiment were statistically significant. However, some trends have emerged none-the-less and can provide some preliminary direction.

It appears from the top and bottom rightmost graphs, that, especially in competitive environments, individuals will "penalize" or lend less support to Latin Americans they met at the local community center, but not non-Latin Americans nor those from their hometown. This aligns only partially with Hypothesis 3A. On one hand, in a job shortage, immigrants may be reticent to support newcomers, especially ones they don't already know (Ryan et al., 2008). If the job shortage is in a sector that mainly caters to immigrants, they may not feel the same resistance to referring a non-Latino immigrant. On the other hand, they may feel a desire to help immigrants from their hometown, due to social pressure either from their community or their friends and family back home (Coleman, 1988; Portes, 1998). These concurrent pressures may produce the "V" shape result seen in those graphs. Further, it appears that when there is no job shortage, immigrant connection does not affect how much job support is recommended.

The bottom left graph in Figure 16 shows that, in a job shortage, respondents are less likely to recommend that: *Juan should explain to Daniel how to apply to this job, including where to send his resumé* when Juan and Daniel are both immigrants from the same hometown than when Daniel is a non-Latin American immigrant. This finding is in line with H3A, that competition will lower job supports among immigrants as has been shown in other contexts (Epstein, 2008; Ryan et al., 2008). While it is not clear why we do not see the same patterns we see in the bottom left graph as we do in bottom middle and bottom right, it could be that explaining to Daniel how to apply would be both imperceptible and a basic form of support and thus not invite any social sanctioning from other members of the community or from Juan's hometown. However, not being encouraging and overtly positive, could be perceived as a slight, and thus in a community characterised by social closure would be subject to social sanctioning. Finally, because the differences between groups are not statistically significant, more evidence is required to determine whether H3A can or cannot be rejected.

3.6 Discussion and Conclusion

This paper studied the relationship between co-ethnic identity, networks, and job search support. The work in this area that explores migrant job referral networks focuses mainly on the job searcher side. We propose here that understanding the referral side of the job search process can uncover important insights into how ethnic or migrant solidarity operates at an individual level to produce observed employment outcomes. For one, the decision to help a fellow migrant reveals a tension between solidarity on one hand and recommender risk and reputation on the other. This is particularly salient for migrants who tend to have denser networks that foster social monitoring, meaning reputation can be especially salient (Coleman, 1988). Also, solidarity or in-group effects are expected to be stronger among migrants than for other groups, due in part to the social capital inherent in these networks (Portes, 1998). Simultaneously, the existence of a migrant network can imply competition, particularly in cases where there are few jobs (Ryan et al., 2008). This would suggest that job referral networks may look different for migrants than for other groups. Our focus was on when and under what circumstances a migrant would be willing to refer a fellow newcomer which led to three broad findings.

First, we found that immigrants are more likely to lend job support to each other, compared to non-Latin Americans. This result holds across two experimental vignettes, one presenting a situation where the candidate was "risky", and the other where there was a slack labor market and thus competition for jobs. We find a statistically significant difference between likelihood of support to non-Latino Americans versus Latino Americans, but no difference between whether the candidate and the job seeker where from the same hometown or not.

Second, we looked at the relationship between provision of job support, reputational risk of the job candidate, and connection type. We find strong support for the hypothesis that immigrants would prefer to lend support to lower risk candidates compared to higher risk candidates. However, we also show that the negative effect of a reputational risk, such as a previous firing, can be partially offset by a closer immigrant connection (being from the same hometown), in some cases, completely eliminating the effect of a reputational risk. This appears to be most salient in contexts where there is strong immigrant community unity. In our sample of Latin American immigrants from the Raleigh-Durham area, we instead find that being from the same home country can exacerbate the effect of "risk". In this case, reputational risk appears more salient than home country unity.

Third, we explore job search support in a situation of competition, where there are few jobs and the job helper himself is looking for work. In our sample of immigrants from the Raleigh-Durham area, we find some preliminary evidence that a job shortage may lead to lower job search support among Latin American immigrants that are not from the same home country. However, in the online Lucid sample, we find that, despite the competitive environment, individuals are more likely to recommend support to a fellow immigrant than a non-Latin American. The latter finding runs counter to previous literature on inter-immigrant support in competitive environments (Ryan et al., 2008), but instead supports findings that slack labor markets can lead to increased referrals (Bond & Fernandez, 2019).

A couple of issues remain in fully understanding the link between immigration and support offered to job candidates. Firstly, there may be concerns that this lab-in-the-field type experiment would not replicate in a real-world scenario. This is a valid concern, particularly because vignette experiments may not accurately convey the pressures exuded by social monitoring, and respondents may thus be subject so social desirability bias. However, at the same time, respondents may not internalize the true risk that a candidate with a poor reputation may offer. Because of these competing factors, it is not clear in what direction the results may be biased, and further observational or survey research will need to tackle this point.

Secondly, while the findings are internally valid, there may be concerns about making any out of sample predictions. The first sample used was a convenience sample drawn from online survey platforms which can induce bias towards more technically-savvy immigrants, who may have specific job search habits like using the internet as their primary means of search. We note above that the sample is more female, better educated, and younger than the average Latin American in the American Community Survey. It is also possible that choice to earn money on these platforms is influenced by network contacts, if people tell their friends about this opportunity. Thus, we may only be observing a portion of the Latino immigrant network, or specific networks, which can threaten external validity, especially with network-based questions. The same issues may arise with Sample 2. While we drew the sample using more personal means (direct contact or contact through local Facebook groups), the sample is still younger and better educated than the ACS average for the area. Therefore, we cannot make inference to the overall Latin American-born population in the United States or the Raleigh-Durham area. However, this study presents a solid starting point for studies with representative samples to explore these topics and understand what characteristics may (or may not) be involved in the decision of when to help a fellow immigrant.

The study of migrant integration is rapidly becoming an important policy issue facing the international community. As the number of forced migrants continues to grow in contexts of worsening economic and political strife, understanding how immigrants find jobs in a new destination is more important than ever. Studying this through the lens of job-referrals means positioning the immigrant as both a source of and a seeker of help, a framework that is rarely used but is crucial to understanding immigrant integration. Furthermore, by shedding light on the circumstances under which migrants fail to help each other, we highlight the most vulnerable immigrants: those who do not receive help from their peers.

Conclusions

This dissertation examines how migrants' social ties affects their access to social capital which can help or hinder them in their goal to integrate and find work. The papers herein present the many "faces" of networks. Namely, while networks are useful and sometimes crucial for newcomers, they may also constrain and limit opportunities.

First, In Chapter 1, I study Colombian return immigrants from Venezuela and find that they are more likely to use their networks to find jobs than other immigrants. Indeed, this is evidence that social capital is being accessed through ties. However, this is not a panacea for migrant reintegration. I also show that jobs found through networks are lower quality on average than those found through other means, and return migrants appear to be using their networks as a last resort. This points to evidence that their networks may not be endowed with many resources or high status.

In Chapter 2, we study Chinese immigrants to the US and we similarly find that connections to both co-ethnic and majority networks is associated with positive assimilation indicators, like satisfaction with life in the USA or desire to adapt to American culture. However, immigrants with fewer ties to the majority or mainly coworker-based co-ethnic networks have achieved economic success. These findings indicate that the relationship between co-ethnic and majority ties and immigrant incorporation is non-linear, multi-faceted and can differ greatly even within the same immigrant group.

In Chapter 3, I study the limits of ethnic solidarity in job searching, and whether social ties can help overcome gaps in intra-ethnic support provision. I administer a factorial survey using vignettes to Latin American immigrants in the USA. I show that there are two factors that can lead individuals to feel reticent to provide a job referral or job search support: when the candidate poses a reputational risk and when there is competition for jobs. In the former case, a home country or ethnic connection is not enough to overcome the risk of a reputational loss. In fact, in one sample, this connection *exacerbates* the effect of a reputational risk on the provision of job support. In the latter case, I show that in a job shortage, individuals are willing to help friends but less likely to help strangers. This shows that while network ties (particularly strong ones) can facilitate the job search process, especially in a difficult environment, ethnic solidarity or hometown connections are either insufficient or harmful in certain cases.

Overall, this research shows that context shapes the association between social networks and immigrant (re-)incorporation. I contribute to a growing literature on two key fronts. First, I join other migration scholars in finding that immigrant and return migrant experiences and assimilation trajectories are heterogeneous and one-size-fits all policies or approaches will not accurately capture this diversity. I show that one of the fundamental ways in which immigrants diverge is on the composition and structure of their personal networks and this is associated with their employment outcomes. Second, I show that the migration experience at destination is important for understanding incorporation. Whether individuals at destination are willing to refer a stranger, have access to or knowledge of jobs, or work in environments with immigrants, plays an important role in immigrant outcomes. For policymakers and migrant support organizations, this work highlights the specific ways in which they can alleviate job market pressures and help incorporate migrants and return migrants into their communities. More specifically, my findings can help target vulnerable migrants who may not have access to support systems to aid their incorporation.

Appendix A

Table A. 1: DID Models of Relationship Between Use of Networks and Return Migrant Status: Placebo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ret. Mig.	0.12***	0.07***	0.08***	0.13***	0.08***	0.08***	0.13***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
year=2014	-0.13***	-0.10**	-0.10**						
	(0.03)	(0.03)	(0.03)						
Ret. Mig.*2014	-0.02	-0.02	-0.02						
	(0.04)	(0.04)	(0.04)	0.05**	0.04*	0.04*			
year=2016									
				(0.02)	(0.02)	(0.02)			
Ret. Mig. *2016				-0.02	-0.02	-0.02			
				(0.02)	(0.02)	(0.02)	0.05**	0.03*	0.03*
year=2017									
							(0.02)	(0.02)	(0.02)
Ret.Mig.*2017							-0.03	-0.02	-0.02
	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	(0.04)	(0.04)	(0.04)
Age (years)							-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.02***	0.02***	0.02***	-0.02***	0.02***	0.02***	-0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	-0.06***	-0.03***	-0.03***	-0.06***	-0.03***	-0.03***	-0.07***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Education		-0.09***	-0.09***		-0.09***	-0.09***		-0.09***	-0.09***
HS or less									
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Tertiary or more		-0.33***	-0.32***		-0.32***	-0.32***		-0.33***	-0.32***
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Household Size			0.00***			0.00***			0.01***
			(0.00)			(0.00)			(0.00)
Observations	154567	154555	154555	147851	147839	147839	94381	94372	94372

Notes: Coefficients from linear probability models. Standard errors in parentheses. Return Migrant indicates an individual in the sample returned from Venezuela. 2014 indicates individual found their job in 2014, 2016 indicates individual found their job in 2016, and so on. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household over age of 12 [verify exact age]. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

Table A. 2: Robustness Checks of Relationship Between Return Migration and Using Networks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Returned past 5 years	Returned past 5 yrs or 1 yr	Full sample	US/EU returnees as control	Neighbor country returnees	Work as reason for leaving	Omit hhld of returnees
Ret. from Ven. past 5 years	0.07***						
	(0.01)						
Ret. from Ven. past 5y or 1y		0.07***					
		(0.01)					
Ret. from Ven. past year			0.10***	0.06*	0.06*	0.11***	0.10***
			(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Age (years)	-0.01***	-0.01	-0.01***	-0.01	-0.01	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	0.00***	0.00+	0.00***	0.00+	0.00+	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.02***	0.03	0.02***	0.03	0.03	0.02***	0.02***
	(0.00)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
Married	-0.03***	-0.03	-0.03***	-0.04	-0.04	-0.03***	-0.03***
	(0.00)	(0.03)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
Education							
No education	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
HS or less	-0.10***	-0.08*	-0.10***	-0.08*	-0.08*	-0.10***	-0.10***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)
Tertiary or more	-0.35***	-0.30***	-0.35***	-0.30***	-0.30***	-0.35***	-0.35***
	(0.01)	(0.05)	(0.01)	(0.05)	(0.05)	(0.01)	(0.01)
Household							
Household Size	0.01***	-0.00	0.01***	-0.00	-0.00	0.01***	0.01***

	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.06***	0.77*	1.06***	0.77*	0.77*	1.06***	1.06***
	(0.02)	(0.39)	(0.02)	(0.39)	(0.39)	(0.02)	(0.02)
Month f.e.	YES	YES	YES	YES	YES	YES	YES
Department f.e.	YES	YES	YES	YES	YES	YES	YES
Observations	230179	228756	231468	1681	1681	230179	228756

Notes: Coefficients from linear probability models. Standard errors in parentheses. Ret. from Ven. indicates an individual in the sample returned from Venezuela. Past yr indicates the individual returned in the past year and past 5 years indicates the individual returned in the past 5 years but not in the past year. See text for details on model specifications. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

Table A. 3: DID Models of Relationship Between Use of Networks To Find Job and Being a Recent Return Migrant

	(1) Returned past 1 year	(2) Returned past 5 years	(3) Full sample	(4) US/EU returnees as control	(5) Neighbor country returnees	(6) Work as reason for leaving	(7) Omit hhld of returnees
2015	0.06***	0.04**	0.05***	-0.22**	0.48***	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(0.07)	(0.09)	(0.01)	(0.01)
Ret. from Ven. (past yr only)	0.10***						
	(0.02)						
Ret. from Ven. (past yr only) * 2015	0.03						
	(0.05)						
Ret. from Ven. (past 5 y)		0.04**					
		(0.01)					
Ret. from Ven. (past 5 y) * 2015		0.07*					
		(0.03)					
Ret. from Ven.			0.06***	0.06+	0.02	0.12***	0.07***
			(0.01)	(0.04)	(0.04)	(0.02)	(0.01)
Ret. from Ven. * 2015			0.05*	0.06	0.12+	0.01	0.05*
			(0.02)	(0.06)	(0.07)	(0.08)	(0.02)
Age (years)	-0.01***	-0.01***	-0.01***	-0.01	-0.01	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	0.00***	0.00***	0.00***	0.00+	0.00+	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.02***	0.02***	0.02***	0.02	0.05*	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
Married	-0.03***	-0.03***	-0.03***	-0.01	-0.03	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
No education	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.

HS or less	-0.10***	-0.10***	-0.10***	-0.09**	-0.09*	-0.10***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)
Tertiary or more	-0.35***	-0.34***	-0.35***	-0.29***	-0.30***	-0.34***	-0.34***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.01)	(0.01)
Household size	0.01***	0.00***	0.01***	0.00	-0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.06***	1.07***	1.06***	1.17***	0.46***	1.07***	1.07***
	(0.02)	(0.02)	(0.02)	(0.10)	(0.12)	(0.02)	(0.02)
Month f.e.	YES	YES	YES	YES	YES	YES	YES
Department f.e.	YES	YES	YES	YES	YES	YES	YES
Observations	230179	189050	231468	2184	1999	188186	188500

Notes: Coefficients from linear probability models. Standard errors in parentheses. Ret. from Ven. indicates an individual in the sample returned from Venezuela. (past yr only) indicates the individual returned in the past year and (past 5 yrs only) indicates the individual returned in the past 5 years but not in the past year. 2015 indicates individual found their job in 2015, details in text. See text for details on model specifications. Base category for Female coefficient is male. Base category for Married is any condition equivalent to unmarried. Education classified into three categories, No education (base category), High School or less, and at least Tertiary. Household size measured in number of people in household. Month f.e. indicates fixed effects for month job was obtained, department f.e. indicates fixed effects for Colombian department.

Appendix B

Robustness – Multiple Imputation

Of the 513 observations collected in the Chinese Immigrants in the Raleigh Durham Area study, there are 100 observations with missing roster data across all rosters (70 missing Roster A, 72 missing in Roster B and 73 missing in Roster C), with 413 complete observations.

In order to generate a full dataset, we use the following procedure. First, we select only the 34 roster variables from the dataset. Next, we use Multivariate Imputation by Chained Equations implemented using the **mice** package in R (van Buuren, 2021). Missing data is imputed for each column (roster variable) by using all other roster variables as predictors in the model to predict the missing values. This set of variables was chosen because the goal of this study is to see whether demographic characteristics vary based on clusters generated using roster variables. If portions of the roster data were generated based on models that incorporate demographic characteristics, then this may hinder the interpretation of the cluster results.

Using mice, we generate 10 datasets with imputed values for all of the missing roster data. Because the clustering algorithm may generate slightly different clusters with each dataset which would be difficult to reconcile, we took the mean of all imputed variables across 10 datasets to create a single dataset for imputation.

We then use the same procedure as above (see Methods section), selecting an absolute value of 0.1 as a cut-off for the factor loadings, same as above, which resulted in the following variable list used for clustering Roster B Co-worker, Roster B Friend, Roster B Daily, Roster B Weekly, Roster A Friend, Roster C Friend, Roster A Daily, Roster B Monthly contact, Roster A Co-worker.

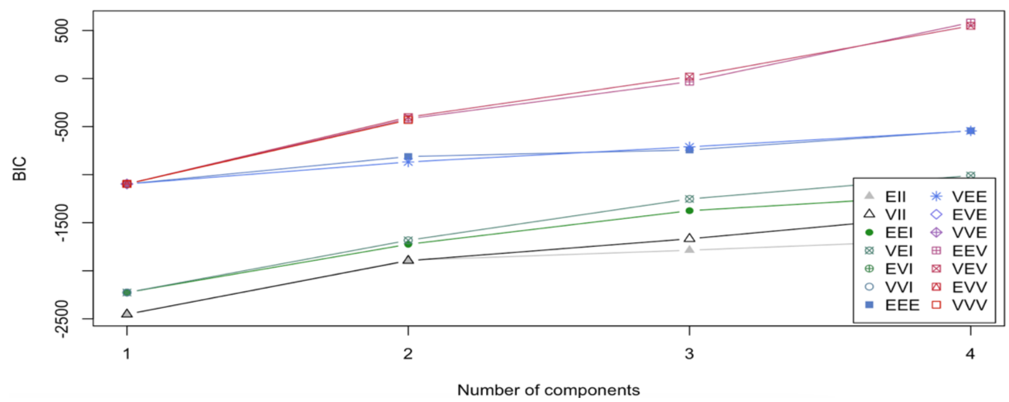

Figure B. 1: BIC Across Model Shapes from 1 to 4 Components from Mclust Package

From Figure B1, we see that the BIC is maximized at 4 components and an EEV model, indicating equal ellipsoidal shape, equal volume and varying orientation. Using the **mclust** package, we obtain the following 4 Clusters (sample sizes): Cluster 1 (58), Cluster 2 (241), Cluster 3 (100), Cluster 4 (114). This echoes the number of clusters seen in the original analysis.

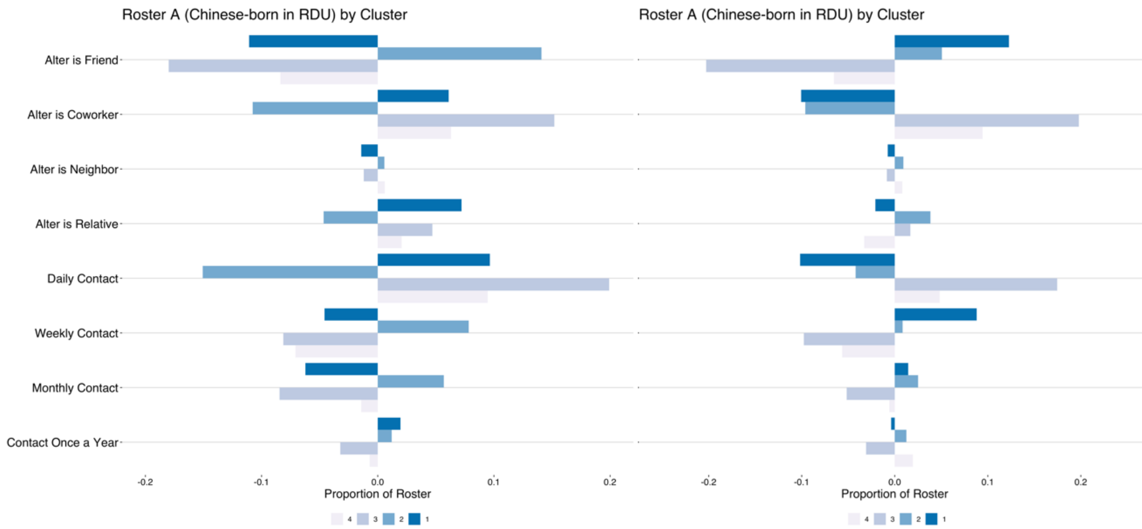

Figure B. 2: Roster A Clusters from Multiple imputation (left) and Original Analysis (right)

Of course, the total sums to 513 because the imputations allow for the full sample to be used. We have aligned the Clusters with the numbers from the original Clustering based on similarity of networks.

We see in Figures B2, B3 and B4, like in the original, individuals in Cluster 2 are most likely to have friends in Roster A, and least likely to have co-workers. In the original, Cluster 1 has a higher proportion of friends than average, and a below-average proportion of co-workers in Roster A. In the new version, Cluster 1 has a higher than average portion of coworkers in Roster A. Furthermore, we see Cluster 3 and 4 are very similar to the original clusters in Roster A.

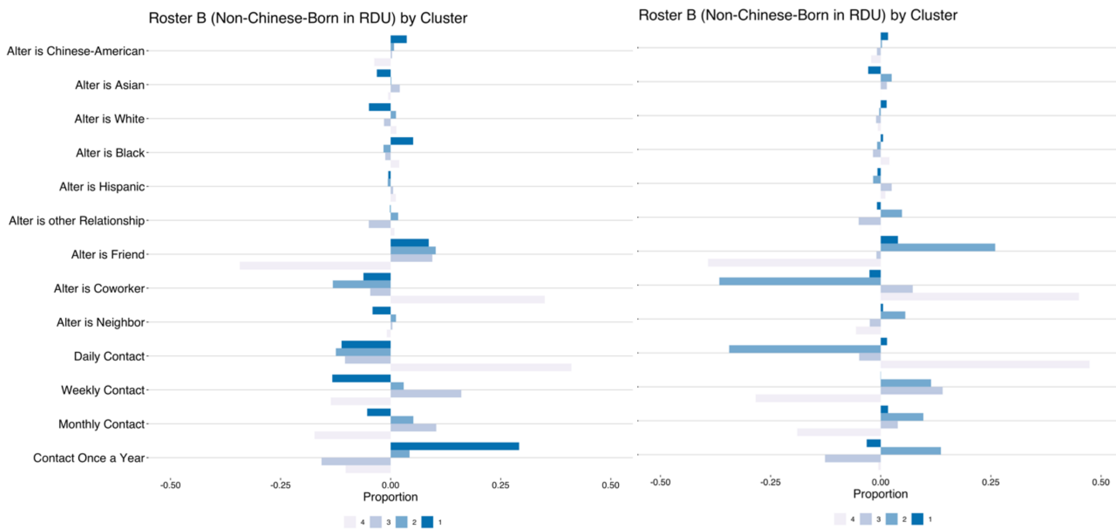

Figure B. 3: Roster B Clusters from Multiple imputation (left) and Original Analysis (right)

For Roster B, we see similar patters between the multiple imputation analysis and the original analysis. For example, Cluster 4 has a much lower than average proportion of friends in Roster B, and has many more than average co-workers. Cluster 3 has an average number of co-workers, similar to the original clusters. They have slightly above average weekly or monthly contact with their ties, like in the original clustering. Cluster 2 nominates the highest proportion of friends and the lowest proportion of co-workers, though the values are less extreme than in the original clusters. In the multiply imputed version, Roster 2 nominates the fewest co-workers, but not none. This indicates some incorporation at work for Cluster 2, but still the lowest of all the clusters. We also find that Cluster 1 has more frequent contact with their Roster B connections in the original analysis than the multiply imputed one. This is relatively unsurprising – lower contact individuals may have been missed from the original Rosters because of recency bias in nominations (Marin, 2004; Marsden, 1993). We see the general patterns remain across most variables despite these discrepancies.

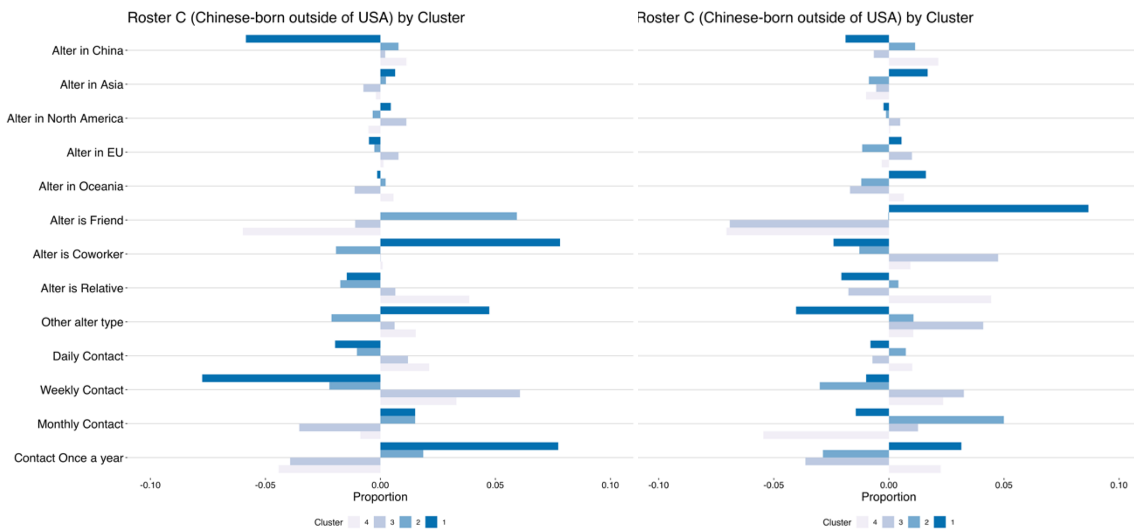

Figure B. 4: Roster C Clusters from Multiple imputation (left) and Original Analysis (right)

In Roster C, we see that, again, the pattern is similar to the original, with slight. Notably, we see lower proportions of friends nominated in Roster C among Cluster 1, and a higher proportion of "co-workers" and "other" alter types. Again, it is possible that various recall biases prompted respondents to be less likely to nominate co-workers or "other" in Roster C. Cluster 2 nominate more friends in the imputed data than the original. Cluster 3 also nominates a larger proportion of co-workers in the original Roster C than in the imputed data.

Table B. 1: Demographic Characteristics by Cluster: Proportions and means (SD)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Demographics				
Age [18-29]	0.245 (0.434)	0.104 (0.306)	0.152 (0.360)	0.079 (0.271)
Age [30-39]	0.132 (0.342)	0.212 (0.409)	0.303 (0.462)	0.281 (0.451)
Age [40-49]	0.321 (0.471)	0.386 (0.488)	0.263 (0.442)	0.351 (0.479)
Age [50-59]	0.170 (0.379)	0.232 (0.423)	0.222 (0.418)	0.211 (0.409)
Age [60+]	0.132 (0.342)	0.066 (0.249)	0.061 (0.240)	0.079 (0.271)
Female	0.517 (0.504)	0.697 (0.460)	0.687 (0.466)	0.596 (0.493)
Married	0.776 (0.421)	0.842 (0.365)	0.790 (0.409)	0.895 (0.308)
Time in US (years)	15.912 (11.43)	13.376 (9.38)	11.099 (8.870)	14.204 (8.55)
Origin				
From Mainland China	0.897 (0.307)	0.896 (0.306)	0.900 (0.302)	0.904 (0.297)
From Hong Kong	0.017 (0.131)	0.008 (0.091)	0.030 (0.171)	0.018 (0.132)
From Taiwan	0.086 (0.283)	0.095 (0.294)	0.070 (0.256)	0.079 (0.271)
Educational Attainment				
High School or less	0.158 (0.368)	0.145 (0.353)	0.121 (0.328)	0.035 (0.186)
Some College	0.053 (0.225)	0.129 (0.335)	0.030 (0.172)	0.035 (0.186)
College	0.193 (0.398)	0.253 (0.436)	0.192 (0.396)	0.159 (0.368)
More than College	0.596 (0.495)	0.473 (0.500)	0.657 (0.477)	0.770 (0.423)
Student/Postdoc	0.103 (0.307)	0.141 (0.349)	0.220 (0.416)	0.140 (0.349)
Currently Employed	0.702 (0.462)	0.589 (0.493)	0.808 (0.396)	0.876 (0.331)
Other Characteristics				
Speaks English Very Well	0.140 (0.350)	0.204 (0.404)	0.172 (0.379)	0.248 (0.434)
Citizen or Green Card	0.897 (0.307)	0.784 (0.412)	0.660 (0.476)	0.789 (0.409)
Has a child over 16	0.607 (0.497)	0.444 (0.499)	0.474 (0.506)	0.373 (0.488)
Belongs to a church	0.368 (0.487)	0.498 (0.501)	0.323 (0.470)	0.325 (0.470)
Owns Property in China	0.161 (0.371)	0.229 (0.421)	0.265 (0.444)	0.159 (0.368)
Intends to Stay in US	0.632 (0.487)	0.589 (0.493)	0.515 (0.502)	0.611 (0.490)
Income (mean, 000s)	110.91 (212.72)	66.30 (49.94)	63.64 (44.34)	86.92 (67.22)
N	58	241	100	114

In Table B1, we see the demographic characteristics by Cluster. The original and the multiply imputed analyses are generally similar, but not identical.

We will start with the analysis of clusters most similar to the original clusters. Cluster 4, *Economically Integrated*, show similar patterns to the original analyses. They are the most likely to be employed, taking over this spot from Cluster 3 in the original analyses. There is strong evidence of incorporation given by a relatively long duration, high levels of English, and the lowest levels of property ownership in China. However, they fall second to Cluster 1 on duration in the US and proportion that hold a green card.

Indeed, the "new" Cluster 1 appears to carry many hallmarks from Cluster 4 (*Economically Integrated)* and Cluster 2 is now the only socially embedded network. In fact, Cluster 1 is the lowest agreement cluster in terms of individuals in both the imputed and original clusters. This cluster has high longevity in the US, the highest proportion of holders of citizenship or green cards, as well as strong intentions to stay. However, we still find that this cluster is middling on proportion currently employed, on proportion with post-grad education, and average age. However, this group now has the longest duration in the USA (previously second-longest), highest proportion with citizenship or Green Card (previously second highest), and the lowest proportion with very good English (previously second lowest).

Cluster 2, “Socially embedded”, remains the Cluster with the lowest proportion with more than college, the lowest likelihood of being currently employed and the highest proportion female and about 50% belong to a church- similar to before. We find a lower portion of this cluster is female, but this declines across all clusters, due to the fact that men are less likely to fill in all the Rosters in our sample.

Cluster 3, *Undecided Newcomers*, remains the cluster who has the lowest duration in the Unites States. While they are now the second-highest educated cluster, they continue to be the least likely to hold a citizenship or a Green Card, the most likely to own property in China, and the lowest intention of staying in the US, strong indicators of their newcomer status. Further, they remain the youngest cluster, with a modal value of 30 to 39.

Overall, we see similar patterns in demographic characteristics across all four Clusters despite some discrepancies, mainly in Cluster 1, which now more closely resembles “Economically Integrated”.

Figures B5 and B6 show the results of regressing assimilation and employment variables on the 4 clusters. We see, in green, means for the clusters from the multiply imputed data. Overall, patterns are similar to the results from the red (original) models. We see that the main findings involving Cluster 2 hold – they are most likely to want to adapt to the USA, are less likely to believe the USA weakens family, have relatively high satisfaction over all (though this finding is now murky), have a low proportion “ever worked in the USA", are the lowest income, and more likely to be paid on an hourly basis.

Cluster 3, *Undecided Newcomers*, also has consistent indicators with previous estimates, they are still the least likely to identify as partly American, and most likely to own a business. However, their overall satisfaction with the USA has increased, likely because they are less likely to see there is a conflict between ethnic groups, and slightly more likely to believe there is no better country than the USA. This is not a large deviation from their profile in the main estimation, namely because recent arrivals both chose the US as their destination and may be shielded from ethnic conflict due to their status.

Cluster 4, *Economically Integrated*, appear similar on every variable, but have a reduced mean for "Identify Partly or Completely as American", whereas this is increased for Cluster 1. This is unsurprising given that Cluster 1 is now the longest duration cluster and has the highest proportion of individuals with Green Cards or citizenship. Indeed, our analysis contends that these factors are likely contributors to identification as American, which can explain the changes in this result.

Cluster 1 from the multiply imputed results show much higher levels of income than in the original analysis, are more likely to say there is "No Better Country", and less likely to "Want to Adapt" to the USA. This remains consistent with their position as embedded networks, but shifts more towards the results of Cluster 4. This is likely due to the fact that Cluster 1 demographics now include a higher duration in the US, like Cluster 4, and lower levels of church attendance, which may indicate lower adherence to American cultural values. Simultaneously, their material success may be correlated with their likelihood of indicating "No Better Country". Indeed, despite the changes in descriptives for Cluster 1, Figures B5 and B6 results confirm the links we find between clusters and assimilation indicators in the paper.

Overall, despite these changes, the results are consistent with the broad typologies identified in the paper: Socially Embedded/Chinese Friendship Networks, Undecided Newcomers and Economically Integrated. Future work using clustering algorithms on immigrant network data may consider using multiple imputations, particularly if a low proportion of the network data is missing.

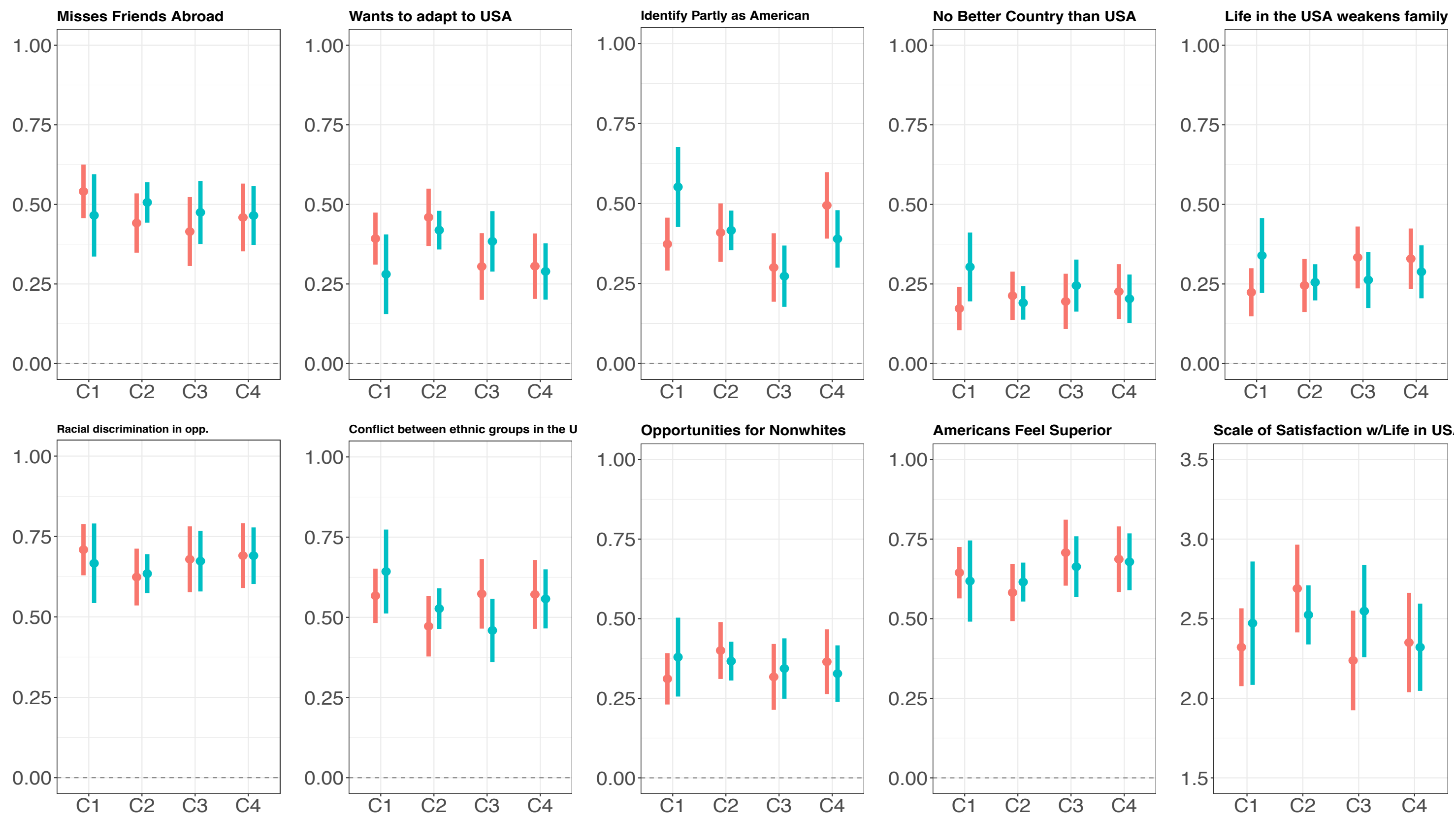

Figure B. 5: Indicators of Assimilation by Cluster (Multiple Imputation Results in Green)

Notes: Values in graphs are coefficients from linear models with Cluster as the main independent variable and without controls. All values coded either 0 or 1, based on whether respondent Agrees (1) or Disagrees (0) with statement. Means in Table B1. Scale of Dissatisfaction obtained by summing: "There is no better country than the USA", "Life in the USA weakens family" (reverse coded), "There is racial discrimination in opportunities" (reverse coded), "There is conflict between ethnic groups in the USA" (reverse coded), "Non-whites have as many opportunities to get ahead economically as whites in the U.S.", and "Americans feel Superior" (reverse coded).

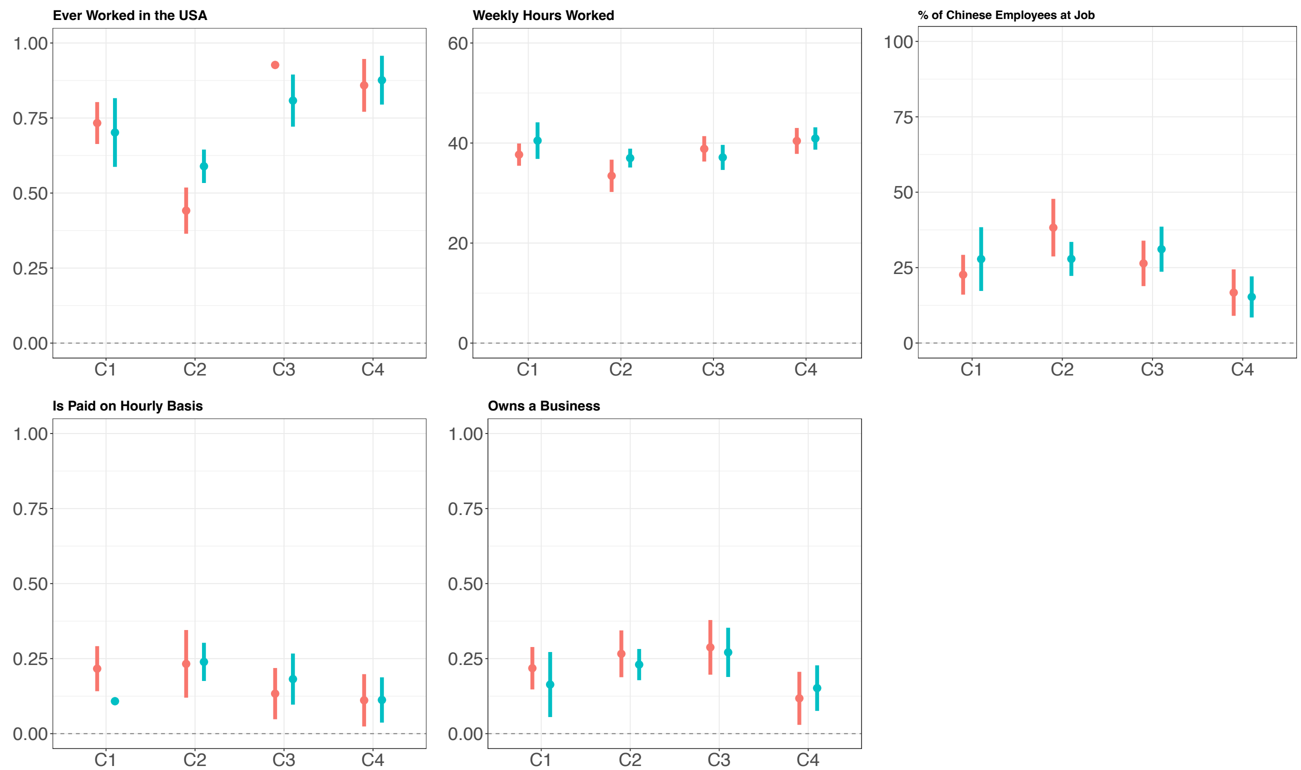

Figure B. 6: Indicators of Employment and Income by Cluster (Multiple Imputation Results in Green)

Notes: Values in graphs are coefficients from linear models with Cluster as the main independent variable and without controls.

Re-clustering

The variable selection process for the clustering can be performed in a number of ways. Above, we used a principal components analysis to select the roster variables that explained the highest amount of variation on the first component. However, it is possible that these are not the most substantively meaningful variables, which may affect the clustering outcomes. Here, we test a researcher-led variable selection process and compare the results to the main results here.

First, we take stock of all the Roster variables to be clustered. Within each Roster question (nature of relationship, frequency of contact, race of contact in Roster B and location of contact in Roster C), we select one variable. This is done so that there is representation of each category, which were chosen because of their relevance to this immigrant group (Merli et al., 2022). Within Roster A, we select proportion Friend and proportion daily contact. Friendship ties have been shown to be important in incorporation (Min & Kim, 2000). Daily contact in our data is associated with co-worker relationships, so we select this variable to represent another dimension of immigrant social connection. In Roster B, we select proportion friend and proportion daily for the same reasons. We also choose proportion of contacts who are white, because ties to the majority have been shown to affect both labor market and social assimilation (Lancee, 2012; Min & Kim, 2000). For Roster C, we select proportion of contacts who are relatives, who they speak to yearly and who are in China. We chose relatives based on other works that show that ties to family affect self-identification (Lubbers et al., 2007) and that contacts spoke to family ties at origin more frequently than to friendship ties (Mouw et al., 2014). We thus also included proportion of contacts nominated that are in China, and proportion that they speak with yearly, to capture another dimension of Roster C.

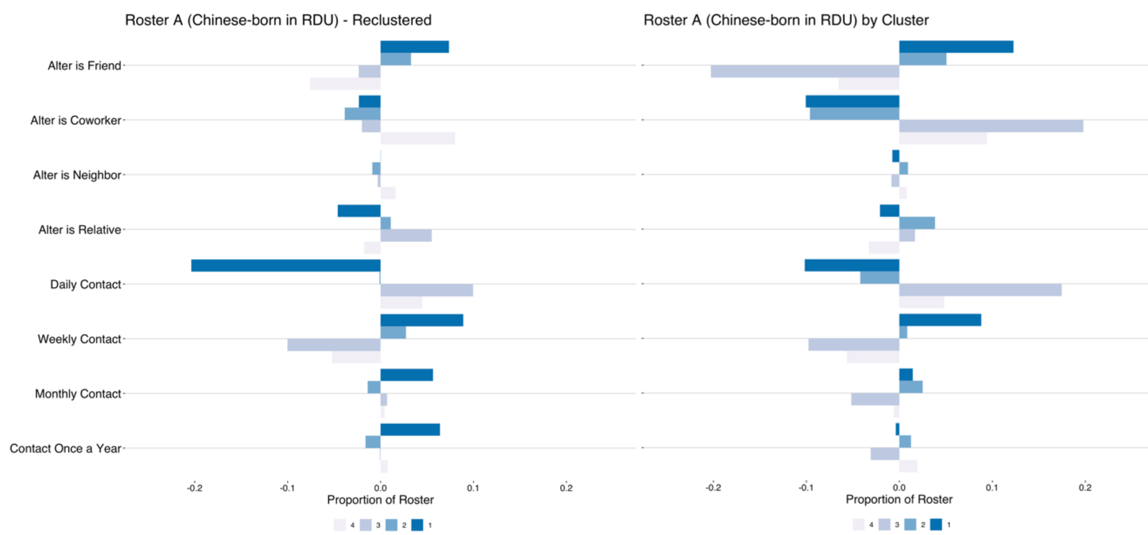

Figure B. 7: Roster A Clusters from Multiple imputation (left) and Original Analysis (right)

We use the same clustering procedure described in the methods section and obtain, again, 4 clusters, which we try to match to the original profiles to align the labels. We get: Cluster 1 (N= 41), Cluster 2 (N=217), Cluster 3 (N=31) and Cluster 4 (N=124).

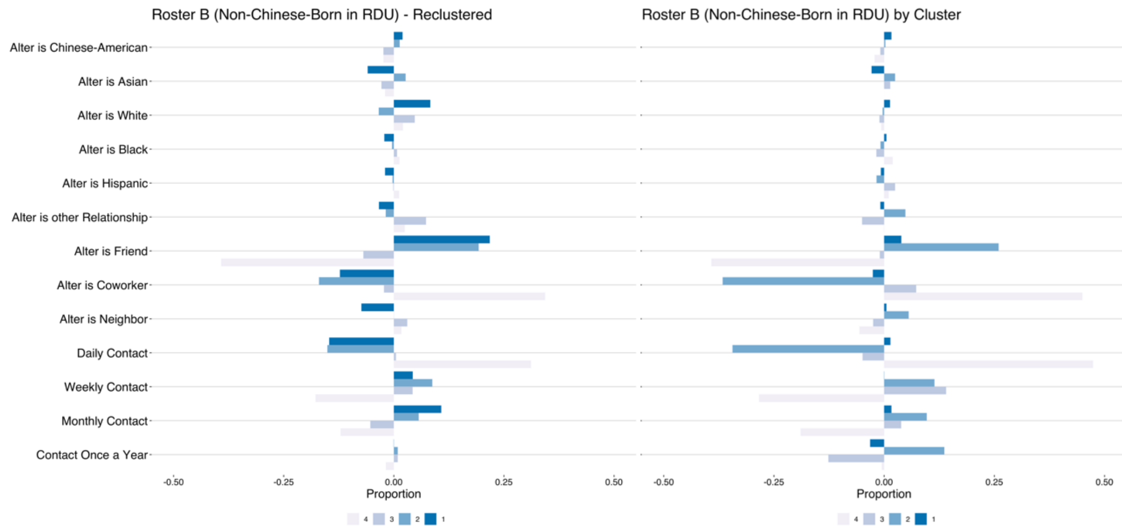

Figure B. 8: Roster B Clusters from Multiple imputation (left) and Original Analysis (right)

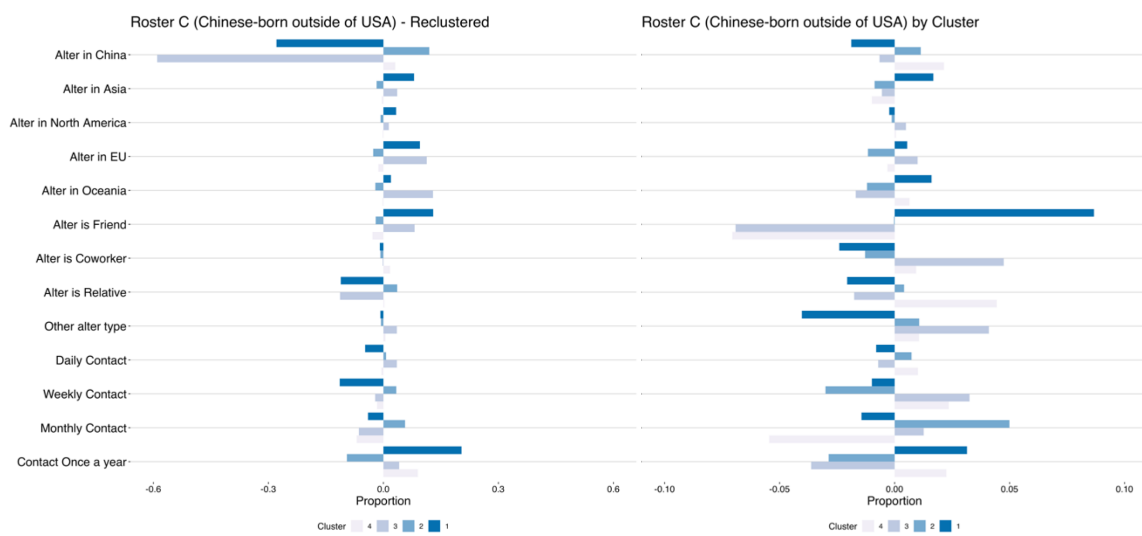

Figure B. 9: Roster C Clusters from Multiple imputation (left) and Original Analysis (right)

We see very similar patterns emerge from this new variable selection. Cluster 1 remains a group characterized by Chinese Friendships, but also nominates the most friends in Roster B. Cluster 2 nominates a higher-than-average proportion of friends in Roster B, and the lowest proportion of co-workers in Roster B. Cluster 3 diverges somewhat from the original, with more balance between friends and coworkers than the original cluster in Roster A, but with a similar balance in Roster B. Lastly, Cluster 4 remains characterized by nominating coworkers in Roster A, though with more balance in Roster B.

While the descriptives are not identical to the original clustering, the same broad patterns emerge. Cluster 4 is high earning, the most likely to have a Green Card or citizenship, highly educated and has high English levels (though, second to the new Cluster 1).

Cluster 3 is high earning, highly educated, the second shortest time in the US, and the most likely to own property in China. This cluster diverges somewhat from the original Cluster 3, mainly in that they have the highest intention to stay in the US and they are the least likely to be students or post-docs. This is likely due to the fact that Cluster 3's networks are far less co-worker based than the original. Regardless, while they may not be "undecided" they are still relative newcomers, have maintained ties to China and, despite their intention to stay, are the second least likely to have a green card or citizenship.

Table B. 2: Demographic Characteristics by Cluster: Proportions and means (SD)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Demographics				
Age [18-29]	0.146 (0.358)	0.148 (0.356)	0.032 (0.180)	0.081 (0.273)
Age [30-39]	0.293 (0.461)	0.231 (0.423)	0.323 (0.475)	0.226 (0.420)
Age [40-49]	0.317 (0.471)	0.338 (0.474)	0.452 (0.506)	0.419 (0.495)
Age [50-59]	0.220 (0.419)	0.222 (0.417)	0.161 (0.374)	0.202 (0.403)
Age [60+]	0.024 (0.156)	0.060 (0.238)	0.032 (0.180)	0.073 (0.260)
Female	0.561 (0.502)	0.691 (0.463)	0.677 (0.475)	0.597 (0.493)
Married	0.732 (0.449)	0.829 (0.377)	0.903 (0.301)	0.895 (0.308)
Time in US (years)	13.539 (9.025)	12.322 (9.458)	12.946 (8.931)	14.249 (8.150)
Origin				
From Mainland China	0.902 (0.300)	0.908 (0.290)	0.806 (0.402)	0.935 (0.247)
From Hong Kong	0.000 (0.000)	0.009 (0.096)	0.032 (0.180)	0.008 (0.090)
From Taiwan	0.098 (0.300)	0.083 (0.276)	0.161 (0.374)	0.056 (0.232)
Educational Attainment				
High School or less	0.098 (0.300)	0.138 (0.346)	0.032 (0.180)	0.016 (0.126)
Some College	0.073 (0.264)	0.097 (0.296)	0.097 (0.301)	0.065 (0.247)
College	0.195 (0.401)	0.240 (0.428)	0.226 (0.425)	0.194 (0.397)
More than College	0.634 (0.488)	0.525 (0.501)	0.645 (0.486)	0.726 (0.448)
Student/Postdoc	0.293 (0.461)	0.171 (0.377)	0.065 (0.250)	0.137 (0.345)
Currently Employed	0.780 (0.419)	0.622 (0.486)	0.774 (0.425)	0.855 (0.354)
Other Characteristics				
Speaks English Very Well	0.415 (0.499)	0.147 (0.355)	0.226 (0.425)	0.260 (0.441)
Citizen or Green Card	0.805 (0.401)	0.719 (0.451)	0.774 (0.425)	0.823 (0.384)
Has a child over 16	0.200 (0.414)	0.475 (0.502)	0.267 (0.458)	0.375 (0.488)
Belongs to a church	0.537 (0.505)	0.465 (0.500)	0.484 (0.508)	0.298 (0.459)
Owns Property in China	0.171 (0.381)	0.252 (0.435)	0.290 (0.461)	0.169 (0.377)
Intends to Stay in US	0.585 (0.499)	0.535 (0.500)	0.645 (0.486)	0.621 (0.487)
Income (mean, 000s)	74.54 (44.92)	60.97 (48.38)	80.73 (85.08)	84.49 (58.48)
N	41	217	31	124

Cluster 2 mirrors the original Cluster 2, a lower income, lower education group, with higher likelihood of having a child over 16. They are the least likely to be employed of all the clusters and have the lowest English levels of all. Their networks are characterized by friendships (not co-workers), and they are the most recent arrivals of all clusters, consistent with the idea that this cluster includes parents of adult children who have time for socialization but are less likely to work.

Lastly Cluster 1 is similar to the Cluster 1 “Chinese Friendships” in the original clustering. We see that it is middling on Time in the US, Educational attainment, income and proportion of Citizen and Green Card holders. Indeed, this is similar to the Cluster 1 observed in the paper. However, this group now has the highest proportion of people who speak *English very well* which may be due to the fact that there are a higher number of students and postdocs in this group than in the original clusters.

In sum, research-informed variable selection for model-based clustering does change the assignment of individuals into clusters. However, because the algorithm both detected the same optimal number of clusters and the same broad patterns of connections, the themes of the four original clusters emerged none-the-less.

Appendix C

Table C. 1: Balance Table: Balance of Control Variables over Main Treatment Conditions (Sample 1)

	Risk Condition (Vignette 1)			Job Shortage Condition (Vignette 2)		
	Risk = Low N=196	Risk=High N=196	p-val	Tie = Low N=190	Tie = High N=202	p-val
Demographics						
Age	32.00 (10.940)	33.20 (11.372)	0.68	32.386 (11.516)	32.800 (10.839)	0.71
Female	0.648 (0.479)	0.679 (0.468)	0.89	0.700 (0.459)	0.629 (0.484)	0.14
Hispanic	0.954 (0.210)	0.980 (0.142)	0.85	0.963 (0.189)	0.970 (0.170)	0.69
Married	0.449 (0.499)	0.464 (0.500)	0.93	0.432 (0.497)	0.480 (0.501)	0.34
Years in USA	15.786 (11.319)	16.582 (11.646)	0.68	16.016 (11.850)	16.342 (11.141)	0.78
Education						
Basic Technical , High School or Less	0.403 (0.492)	0.362 (0.482)	0.41	0.405 (0.492)	0.361 (0.482)	0.37
Advanced Technical	0.122 (0.329)	0.199 (0.400)	0.04	0.184 (0.389)	0.139 (0.346)	0.22
College Degree	0.321 (0.468)	0.291 (0.455)	0.51	0.279 (0.450)	0.332 (0.472)	0.26
Master's Degree or Above	0.153 (0.361)	0.148 (0.356)	0.89	0.132 (0.339)	0.168 (0.375)	0.31
Currently in School	0.276 (0.448)	0.281 (0.450)	0.91	0.263 (0.442)	0.292 (0.456)	0.52
Employment						
First Job in Private Sector	0.643 (0.480)	0.724 (0.448)	0.08	0.674 (0.470)	0.693 (0.462)	0.68
Current Job in Private Sector	0.454 (0.499)	0.495 (0.501)	0.42	0.463 (0.500)	0.485 (0.501)	0.66
Currently Employed	0.842 (0.366)	0.832 (0.375)	0.79	0.832 (0.375)	0.842 (0.366)	0.79

Table C. 2: Balance Table 2: Balance of Control Variables over Main Treatment Conditions (Sample 2)

	Risk Condition (Vignette 1)			Job Shortage Condition (Vignette 3)		
	Risk = Low N=59	Risk=High N=50	p-val	No Job Shortage N=46	High Job Shortage N=63	p-val
Demographics						
Age	33.83 (7.719)	32.74 (5.349)	0.405	32.46 (5.580)	33.94 (7.412)	0.714
Female	0.525 (0.504)	0.380 (0.490)	0.131	0.457 (0.504)	0.460 (0.502)	0.136
Hispanic	0.983 (0.130)	1.000 (0.000)	0.36	0.978 (0.147)	1.000 (0.000)	0.694
Married	0.729 (0.448)	0.800 (0.404)	0.39	0.761 (0.431)	0.762 (0.429)	0.335
Years in USA	9.429 (6.185)	7.191 (6.720)	0.082	7.791 (5.562)	8.850 (7.109)	0.779
Education						
Basic Technical, High School or Less	0.271 (0.448)	0.060 (0.240)	0.003	0.196 (0.401)	0.159 (0.368)	0.373
Advanced Technical	0.119 (0.326)	0.100 (0.303)	0.759	0.130 (0.341)	0.095 (0.296)	0.22
College Degree	0.390 (0.492)	0.420 (0.499)	0.752	0.435 (0.501)	0.381 (0.490)	0.259
Master's Degree or Above	0.220 (0.418)	0.420 (0.499)	0.025	0.239 (0.431)	0.365 (0.485)	0.311
Currently in School	0.068 (0.254)	0.040 (0.198)	0.53	0.043 (0.206)	0.063 (0.246)	0.524
Employment						
First Job in Private Sector	0.864 (0.345)	0.940 (0.240)	0.195	0.913 (0.285)	0.889 (0.317)	0.681
Current Job in Private Sector	0.712 (0.457)	0.780 (0.418)	0.422	0.761 (0.431)	0.730 (0.447)	0.664
Currently Employed	0.864 (0.345)	0.920 (0.274)	0.360	0.891 (0.315)	0.889 (0.317)	0.789

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