Exploring the Health Status of Immigrants in the US

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Abstract:

Since the beginning of the 21st century, immigration settlement patterns have started to shift and regions of the US that do not have a long history of sustaining immigration growth are now considered popular immigrant destinations. These changes have implications to various aspects of society including health. We use the Current Population Survey (CPS) to examine the differences of self-reported health of 213,192 foreign born-individuals across 8 types of immigrant destinations. We find that immigrants living in non-traditional immigrant destinations report better health than immigrants living in historical immigrant destinations. This calls to question whether immigration theories regarding the welfare of immigrant populations in historical immigrant destinations downplay the health benefits that may arise from living in new immigrant destinations. The next step of this project is to examine whether community variation in the Immigration and Customs Enforcement (ICE) removals might explain community variation in immigrant health.

Introduction:

The United States is currently undergoing a dramatic shift in immigration and immigrant settlement patterns, which may have important implications for our understanding of immigrant health. Today, 13.4% of the total population in the US is foreign-born and approximately 46% of all immigrants live in California, Texas and New York (Pew Research Center, 2017). Overall, immigrants are mostly concentrated in 20 metro areas in the US (Pew Research Center, 2017), but in the past 30 years, the foreign-born population has grown in regions that are not considered historical immigrant destinations. For instance, the immigrant population in metro areas in North

Carolina, Oregon, Missouri, Virginia, Washington, and Massachusetts has increased dramatically in the early 20th century (Hall, 2011).

Marrow (2005) explained that the distribution of immigrant populations across the US is changing and new regions are becoming popular destinations. Recent reports show that immigrants from Latin America are decreasing; whereas, immigrants from Asia are increasing. In fact, the highest shares of immigrants coming to the US in 2015 are now from India, followed by Mexico, China, and Canada (Pew Research Center, 2017). The changes in immigration growth and concentration have led to an interest in studying the benefits and negative consequences from living in areas that are not considered historical immigrant destinations, such as Los Angeles, New York City, and Chicago.

Historical immigrant destinations are regions that have continuously received and sustained large shares of immigrants over the course of the 20th century (Hall et al., 2011). These areas may pose several benefits for foreign-born populations because they have well established immigrant communities. For instance, cities with long histories of immigrant settlements may have developed resources to assist and protect the new populations; while cities like Columbus, OH, which has experienced a recent and rapid growth in the percentage of foreign-born individuals, may lack the adequate resources to address the needs of the new residents. Historical immigrant destinations also have well established ethnic enclaves or communities that have a high concentration of a particular ethnic group, which have been shown to be important for the health of immigrants (Tran et al., 2000).

The purpose of this study is to explore health variation among immigrants in the United States, with particular attention paid to examining differing patterns of self-reported health among foreign-born individuals living in new and old immigrant destinations. We use the proposed immigrant destination typology of Hall et al. (2011) and classify 100 different metro areas into 8 types of immigrant destinations in the US. We develop hypotheses regarding community variation in immigrant health based on the literature concerning the health benefits of immigrant enclaves, as well as literature focused on compositional differences among immigrants in these destinations. We first explore baseline differences in the health of immigrants in these areas. We then examine the extent to which baseline differences in immigrant health are driven by compositional features of these different immigrant populations. Second, we seek to determine if higher levels of Immigration and Customs Enforcement (ICE) removals contribute to worse self-reported health among foreign-born individuals across these immigrant destinations.

Ethnic enclaves:

Ethnic enclaves are commonly considered an essential asset for immigrants because these geographic locations can facilitate the formation of social networks with residents who can provide information about the labor market, schools, and other opportunities (Edin et al., 2003). However, competing hypotheses state that ethnic enclaves decrease the interaction with natives and the ability to acquire language skills (Edin et al., 2003). Living in ethnic enclaves may contribute to discrimination in the housing market and a surplus of workers in areas that lack employment opportunities. This latter situation is known as the spatial mismatch hypothesis (SMH) (see Kain, 1968). SMH emphasizes the notion that housing market segregation creates a surplus of workers, and these circumstances could lead to lower wages and higher unemployment rates (Ihlanfeldt & Sjoquist, 1998).

Ethnic enclaves also present several benefits for the immigrant population. The “enclave thesis” states that immigrants may benefit if they work in ethnic enclaves (Xie & Gough, 2011;

Portes & Jensen, 1987, 1989, 1992). For instance, Portes (1987) explained that ethnic enclaves provide access-to-start-up capital, such as rotating card institutions, producer cooperatives, loan associations, and ethnic chambers of commerce. As immigrants continue to arrive, these organizations grow and promote minority entrepreneurship. Previous studies found that positive or negative effects of enclaves depend on the quality of these communities (Edin et al., 2003). Specifically, immigrants living in enclaves with high earnings benefit more from living in there compared to immigrants who reside in enclaves with less than average earnings (Edin et al., 2003). Moreover, other studies have emphasized that ethnic enclaves are beneficial for members of a community when skilled members of the ethnic group remain in the enclave (Borjas, 1998).

Previous studies have also examined the benefits that ethnic enclaves have for specific immigrant groups (Xie & Gough, 2011). For example, Xie and Gough (2011) conducted a study on the economic outcomes of immigrants working in ethnic enclaves versus immigrants working in the mainstream economy and built three measures of ethnic enclaves. Using the New Immigration Survey (NIS), the first measure was constructed based on the ethnic and foreign-born composition of respondents' neighborhoods. The second measure addressed whether respondents speak English in the workplace, and the third measure combined the ethnic and foreign-born composition with language spoken at work. Xie and Gough (2011) found that Hispanic and Asian immigrants that work in places where non-English languages are spoken earn less than Hispanic and Asian immigrants that work in places where English is spoken. Further analyses show that Chinese immigrants earn more in residential areas where other Chinese individuals live and Dominicans earn less when they work in places where non-English languages are spoken. These findings suggest that ethnic enclaves seem to be beneficial only for certain groups; whereas, enclaves may in fact harm economic advancement for other groups.

In regards to the association between living in ethnic enclaves and health outcomes, previous research shows that ethnic enclaves protect older immigrants who are more likely to suffer mental health problems as a result of linguistic barriers, absence of family, and social support, and physical infirmities (Tran et al., 2000). Pumariega et al. (2005) explained that in order to provide better health care services and validate the traumatic events experienced by immigrants and refugees, clinicians should speak the same language as the patients and be willing to support indigenous religious and culturally prescribed practices. Therefore, immigrants living in ethnic enclaves may enjoy a wider access to health institutions and health specialists who speak the same language as them.

Ethnic enclaves also benefit immigrants by providing culturally relevant resources like staple food items and accessible social services; however, neighborhood poverty may have a strong and negative impact on the health of the residents regardless of these factors (Osypuk et al., 2009). In fact, Osypuk et al. (2009) conducted a study on whether immigrant composition was associated with health behaviors in a multi-ethnic study of middle-aged and older adults in four US cities. Osypuk et al. (2009) tested whether certain neighborhood characteristics mediated the association between living in an enclave and health behavior. Using the Multi-Ethnic Study of Atherosclerosis (MESA), Osypuk et al. (2009) found that Hispanic and Chinese immigrants living in neighborhoods with high proportions of immigrants had better dietary intake than other Hispanic and Chinese immigrants living in neighborhoods with lower proportions of immigrants. However, both groups reported worse neighborhood safety, worse social cohesion/trust, and fewer recreational facilities compared to their counterparts living in neighborhoods with lower proportions of Hispanic and Chinese immigrants.

Ethnic enclaves are particular of places that have received a continuous flow of immigrants (Portes, 1987). This is mainly the result of foreign-born individuals building communities with access to ethnic restaurants, groceries, and other establishments as well as social capital that maintain and support the growth of new arrivals (Portes, 1987). Since the great European wave (1880-1930), which was characterized by the migration of more than 23 million Europeans to the US, ethnic enclaves were formed in cities like New York, which received the earlier immigrant waves from Germany, Ireland, Britain, and Poland (Portes & Rumbaut, 2014). Today immigrants come primarily from Center America and Asia, but the formation of ethnic enclaves is still a common occurrence in places like Los Angeles, CA (Portes & Rumbaut, 2014). In recent years, new arrivals have settled in destinations that have not experienced a major influx of immigrants in the same way that Los Angeles, CA or Chicago, IL have. These dynamics are giving birth to new immigrant destinations or gateways like Columbus, OH and Atlanta, GA, but these regions do not have well-established ethnic enclaves like historical immigrant destinations do. Consequently, immigrants cannot enjoy the benefits that come with living in highly concentrated ethnic areas. We expect to see that immigrants living in new immigrant destinations will have worse health than immigrants living in historical immigrant destinations.

New immigrant destinations vs. historical immigrant destinations:

Throughout the past years, there have been dramatic changes in the distribution of immigrants across the United States. These changes led to the influx of immigrants in regions of the US that did not have a long history of immigration settlement and a decrease in the number of immigrants moving to historical destinations like Los Angeles, CA and New York City, NY. Durand et al., (2005) report that the southwest has attracted the majority of Mexican immigrants since the Bracero era of 1942 to 1964. The Bracero Program was an agreement signed by

Mexico and the US in 1942 to allow Mexican contract workers to work for American farms and ranches (Portes & Rumbaut, 2014). The end of the Bracero Program and the passage of the Immigration Reform and Control Act of 1986 (IRCA) marked the beginning of changes in behaviors toward immigrants in the US. There was an increase in the militarization of the San Diego-Tijuana border making California a less popular destination for Mexican immigrants. Also, an increase in unemployment rates due to the post-Cold War recession affected California's economy and led to the passage of Proposition 187 in 1994. Durand et al. (2005) explained that this anti-immigrant regulation prevented undocumented migrants from receiving public social services and required public officials to verify a client's immigration status and report suspected undocumented migrants. These conditions have made California a less popular immigrant destination and may have led to the emergence of new destinations, such as Salt Lake City, Utah.

Historical immigrant destinations have large immigrant populations so they are expected to be fully capable of providing services that address the needs of immigrant individuals more effectively. For instance, with the enactment of Section 201(b) of the Children's Health Insurance Program Reauthorization Act in 2009, states can claim a higher matching rate for translation/interpretation services (Medicaid, 2018), but it is not mandatory to have interpreters working on site. In 2010, the State of California ordered that all health care facilities provide free translation services to patients (Department of Health Care Services, 2010). Since new immigrant destinations have not had the time to develop and establish legislations that mandate translation services, immigrants in these regions could be more prone to suffer from depression, anxiety or other mental health illnesses.

There is little knowledge about the effects of living in new immigrant destinations, but the rapid and recent growth observed in these locations warrants the need to understand the health outcomes associated with residing in these areas. Compared to historical immigrant destinations, new immigrant destinations have experienced a certain level of animosity as it was the case with Atlanta metropolitan area, Georgia (Neal & Bohon, 2004). Neal and Bohon (2004) found that older persons in Atlanta are more likely to believe that immigrants take jobs away and respondents with a high school education or lower are less accepting of immigrants compared to respondents with a college degree or graduate education.

The negative perception of immigrants can exacerbate xenophobic attitudes that influence the immigration enforcement in a community. In fact, King et al. (2012) found that perceptions of crime as a serious problem were positively associated with criminal deportations (i.e., the forced removal of an offender from a certain location). States like Arizona, California, New York and Florida are considered historical immigrant destinations, but they have been ranked in the top ten of states for having the highest levels of criminal deportations since 2006 (TRAC Immigration, 2018). Large numbers of forced removals undoubtedly adds to the need to explore the role these incidents play in the health outcomes of immigrants living in historical immigrant destinations.

Forced removals

Forced removals do not only break down families, but these have the potential to disrupt whole communities by increasing the fear of deportation. In her study of the impact of enforcement policies on Mexican families, Dreby (2012) reported that US born children expressed distress when asked about their parents' immigrant status. Hacker et al. (2011) explained that fear of deportation also affects members of communities who are living in the US legally because they believe that ICE could also question their legal status. Fear of deportation diminishes the collaboration with local law enforcement and the ability to search for health care or apply for health insurance (Hacker et al., 2011). It may also increase depression and hypertension among the immigrant community (Hacker at al., 2011).

The onset of the Great Depression marked the beginning of mass deportations and lower levels of immigration from Latin America to the US (Durand et al., 2005; Pew Research Center, 2017). Consequently, the percent of Asian immigrants coming to the US has been greater than the percent of Hispanic immigrants since 2010. New regions are emerging as popular destinations because the immigrant concentration of different regions in the US continues to change. In fact, following the Great Depression, Illinois has become a major receiver of Mexican immigrants (Durand et al., 2005). Despite these changes, forced removals of undocumented immigrants is still a common occurrence. Therefore, we believe that it is of extreme importance to explore how ICE removals may influence self-rated health of immigrants across different types of immigrant destinations.

Data:

The demographic data derive from the Current Population Survey (CPS) and consist of 213,192 foreign-born individuals across the 100 largest metro areas in the US as defined by the Office of Management and Budget (OMB) in 2009. All data were collected over a period of 10 years, from 2008 to 2017 (see Table 2). Hall et al. (2011) categorized these metro areas into 8 types of immigrant destinations based on historical and current settlement patterns. Former gateways used to be major immigrant destinations but the foreign-born populations in these locations have decreased since 1930. In major-continuous gateways, the percentage of foreign-born individuals has continued to increase and exceed the national average throughout the past century. Minor-continuous gateways also have long histories of continued immigration growth but the share of foreign-born is above or near the national average. Post-World War II gateways are characterized by a rapid growth of the immigrant population since the 1950s.

Re-emerging gateways were popular immigrant destination in the early 20th century, but the immigrant population decreased during the last three decades of this era. At the end of the 20th century, re-emerging gateways experienced a rapid growth of the foreign-born population. Pre-emerging gateways are characterized for having little history of immigration settlement. However, these regions have had a recent and rapid growth of the foreign-born populations. Finally, low-immigration gateways have small foreign-born populations and modest growth of percent foreign-born. Former, major-continuous, minor-continuous, and post-world war II gateways are considered historical immigrant destinations. Emerging, re-emerging, and pre-emerging gateways are categorized as new immigrant destinations. Low-immigration gateways have small and slow-growing immigrant populations, but they are expected to become pre-emerging gateways in the following years (Hall et al., 2011). Overall, there are 8 types of immigrant destinations and these are grouped into historical, new, and low immigrant destinations.

We will utilize data on ICE removals with the purpose of testing how deportations may help explain the differences of health outcomes across immigrant destinations. The ICE Removals under Secure Communities data were acquired via the Transactional Records Access Clearinghouse (TRAC) at Syracuse University. The data include state and county information where the noncitizen was apprehended (TRAC, 2018).

Dependent Variable

The dependent variable is the self-reported health status. We reverse coded the categories into the following: (1) fair, (2) poor, (3) good, (4) very good, and (5) excellent. Self-reported health is highly reliable and widely used as a measure of health status (Krause & Jay, 1994). Acevedo-Garcia et al. (2015) posited that self-rated health is often used to assess immigrant health because it can be applied to populations with young age distributions and is uniformly ascertained, which allows for comparison across datasets. Previous studies documented that self-rated health is a strong predictor of mortality (Idler & Benyamini, 1997). Furthermore, Lumberg and Manderbacka (1996) found that self-rated health assesses health status better than questions that ask about specific health problems. In a study that analyzed the relationship between self-assessed and clinical assessed health and work ability of elderly municipal employees, Eskelinen et al. (1991) found that approximately 61% of the subjects received the same classification for self-assessment of work ability and clinical diagnosis of musculoskeletal capacity. Due to the high reliability of self-reported health, we believe that this is a strong measure of the actual health status of the individuals included in this study.

Overall most of the individuals in the sample report that they have good or better health status (see Table 2). Whereas, approximately 11% of the sample report to have fair or worse health status. The main purpose of this study is to compare the health status of immigrants in the US across different types of immigrant destinations, thus we do not include any native-born individuals in the analysis.

Independent variables

Immigrant destinations (gateways): Our key independent variable is type of immigrant destinations. We utilized the typology created by Hall et al. (2011) in order to classify each major metro area in our sample into the following 8 types of gateways: Former, Post-World War

II, Major continuous, minor-continuous, emerging, re-emerging, pre-emerging, and low immigration metros. In Table 1, we included the complete list of metro areas used in the analysis and the distribution of individuals across these regions. Hall et al. (2011) explained that historical immigrant destinations encompass former, Post-Word War II, major-continuous, and minor continuous gateways. On the other hand, new immigrant destinations or 21st century immigrant destinations include emerging, re-emerging, and pre-emerging gateways (Hall et al., 2011). Low-immigrant destinations have small immigrant populations and do not have a long history of immigrant arrivals. We use Hall and colleagues' typology to create three categories of immigrant destinations in addition to the 8 types described earlier: Historical, new, and low. Los Angeles, CA and New York-Northern New Jersey-Long Island, NY-NJ-PA are categorized as historical immigrant destinations and have the largest number of immigrants among all 100 metro areas: 11.75% and 13.13%, respectively. Table A1 (see appendix) shows that the majority of the sample lives in historical immigrant destinations, while 8.58% of the sample lives in low immigration metros.

Continent of origin: We control for continent of origin as previous research shows that there are differences in health status and preventive behaviors across immigrants based on the region of origin (Allen et al., 2007). Allen et al. (2007) conducted a study using the adolescent portion of the 2001 California Health Interview Survey to explore how immigrants and children of immigrants differed in preventive health behaviors, including nutrition, physical activity, and television viewing or video game playing. The results show that first generation Latinos and Asians had healthier diets than native-born Whites, but Asians consumed more vegetables than Latinos and Latinos consumed more sodas and milk than Asians. First generation immigrants are individuals that were born outside the US and third generation immigrants are individuals that were born in the US but one of the grandparents (from either side of the parents) was born outside the US (Bean et al., 2015). Akresh and Frank (2011) found that compared to immigrants from Mexico, immigrants from all other regions[1] have higher odds of reporting excellent health. In this present study, we use the country of origin to create 7 regions of the world: Oceania, Africa, Asia, Europe, South America, Center America, and North America. Overall, most individuals in the sample are from Center America and Asia (see Table 2). Oceania has the smallest percentage of individuals, followed by North America (i.e., Canada).

Educational attainment and employment status: In order to account for socio-economic status, we control for educational attainment and employment status. Lower socio-economic status is associated with poor health; nevertheless, previous studies found that first-generation immigrants report better health than native born after controlling for socio-economic variables (Akresh & Frank, 2008; Acevedo-Garcia et al., 2010). In fact, Acevedo-Garcia et al. (2010) found that that first-generation Hispanics report better health than third-generation Hispanics after controlling for educational attainment, occupation, and homeownership. Table 2 shows that the majority of the sample is employed. About 30% of individuals report to have less than a high school education, while 28% report to have a bachelor's degree or higher.

Age: We control for age because the age structure of immigrants varies based on location. Immigrants living in states closer to Mexico tend to be much younger than immigrants living in other regions of the US (Hall et al., 2011). Since age is a major determinant of health, any differences we see between individuals that live in historical versus new or low immigration destinations could be the result of the age structure of these populations. In a report released in 2017, the Pew Research Center showed that in 2015, the largest age group shifted from ages 65-

[1] The regions of origin included in the study were South and Central America, Caribbean, Mexico, Western Europe, Canada, Australia, New Zealand, Eastern Europe, Former Soviet Union, Asia, India, Pakistan, Nepal , Bangladesh, Middle East, and Africa.

69 to ages 40-44 among foreign-born individuals. Whereas, the native born population had a more dispersed age structure (Pew Research Center, 2017). After the 1965 Act, which allowed individuals with families in the US to migrate to the US, the number of working age immigrants increased dramatically (Card, 2005). According to the Migration Policy Institute, the majority of immigrants in the US in 2016 were between the ages of 20 and 54. Since many immigrants leave their home countries in search of work, it is not surprising to see that there are more adult immigrants than any other age group.

In Table 2, the age group of 35-50 is the largest, followed by age group of 19-35. Since immigrants are less likely to move to the US with their children, we see a small percentage of individuals between the ages of 0-18. The small percentage of older immigrants (65 and above) could be due to immigrants returning home due to illness. This explanation is known as the salmon bias hypothesis, which emphasizes the notion that selective emigration causes the lower mortality rates observed in immigrant populations in the US, specifically the US Hispanic population (Pablo-Mendez, 1994; Turra & Elo, 2008).

Methods

All statistical analyses were performed with Stata, version 15 (Stata Corp, College Station). We used multivariate ordered logit models to examine the differences of self-reported health status across the 3 types of immigrant destinations (i.e., historical, new, and low). We also conducted additional analyses to observe differences of self-reported health across the 8 types of immigrant destinations that Hall and colleagues developed. Although all of the dependent measures of self-reported health are ranked from poor to excellent, the distance between categories cannot be assumed to be equal (as in interval data). Thus, we first conducted regressions where the health status was ranked from 1 (poor) to 5 (excellent) and immigrant destinations were classified into 3 categories. In the second set of regression, we included the 8 types of immigrant destinations. In the third and fourth set of regressions (not shown), we coded good, very good, and excellent as 1, whereas lower scores were coded as 0. The latter step was conducted with the goal of determining if the findings hold when we use a dependent variable that is binomial instead of an ordinal variable with 5 categories. We use a two-level ordinal logit general model with a random effect for metro areas (individuals nested in metro areas):

Level 1 Model:

$$\eta_{1ij} = \beta_{0j} + \beta_G G + \beta_C C + \beta_E E + \beta_P P + \beta_y Y + D_{4ij}\delta_{4j}$$

Level 2 Model:

$$\beta_{0j} = \gamma_{00} + u_{0j},$$

$$\delta_{4j} = \delta_4$$

where G is the 3 types of immigrant destinations (historical, new, low)[2], C is the nativity group (Oceania, Africa, Asia, Europe, South American, Center American, North American), E is the level of education, which is a categorical variable, P is the employment status, which is a dummy variable, and Y is a series of dummy variables for years. D_{4ij} is an indicator for each category of health status (poor, fair, good, very good, excellent). δ is the threshold and u_{0j} is the random effect. We treat the intercept as random and the remaining coefficients as fixed.

Results

In Table 3, Model 1 shows the results of the unconditional model and helps us assess the magnitude of variation among metro areas in the absence of covariates. Level-1 model is specified as:

$$\eta_{mj} = \beta_{oj} + D_{4ij}\delta_{4j}$$

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[2] G represents the 8 types of immigrant destination in the second set of regressions we conducted.

Where D_{4ij} is a dummy variable indicating whether m=4. At level 2, the model is specified as the following:

$$\beta_{0j} = \gamma_{00} + u_{0j}, \qquad u_{0j} \sim N(0, \tau_{00})$$

$$\delta_{4j} = \delta_4$$

The results indicate that the variance (0.065) across metro areas is significant based on the confidence interval. The reported likelihood-ratio test shows that there is enough variability between metro areas to favor the use of a mixed-effects ordered logistic regression over a standard ordered logistic regression. In Model 2, we include the three types of immigrant destinations and the dummy variables for years. Compared to foreign-born individuals living in historical immigrant destinations, the probability of reporting a higher level of health status is 26% higher ($p<.001$) for foreign-born individuals living in new immigrant destinations while holding years constant. The probability of reporting a higher category of health status is greater for individuals living in low immigrant destinations compared to individuals living in historical immigrant destinations. Interestingly, relative to 2017, the odds ratio of reporting a higher level of health status is greater for all years with the exception of 2008. Controlling for years and types of immigrant destinations explains [((0.065-0.049)/0.065)*100]=24.61% of the variability across metro areas.

In Model 3, we control for the continent of origin, but the magnitude size and level of significance do not change much for types of immigrant destinations. In Model 4 and Model 5, we include educational attainment and employment status, respectively. The results in Model 5 show that the odds ratio of reporting a higher health category continues to be greater and significant for individuals living in new immigrant destinations (1.208, $p<.001$) and low immigrant destinations (1.245, $p<.001$) compared to individuals in historical immigrant destinations. Interestingly, the direction of the coefficients for European and Asian immigrants changed from positive to negative in Model 4, but only the coefficient for Asian immigrants was significant. In other words, compared to Central American immigrants, the probability of reporting to have a higher health status is 5.3% lower ($p<.001$) for Asian immigrants. Once we control for employment status, Asian immigrants have a higher probability of reporting a higher health status category compared to Central American immigrants ($p<.001$).

In Model 6 of Table 3, the magnitude size and level of significance decrease for new immigrant destinations and low immigration destinations once we control for age. Specifically, the probability of reporting to have a higher health status for individuals that live in new immigrant destinations is 11.7% ($p<.05$) and 13.1% ($p<.01$) for individuals that live in low immigration destinations compared to historical immigrant destinations. Relative to individuals in the age group of 35-50, the probability of reporting to be in a higher health status is 46% ($p<.001$) lower for individuals that are between the ages of 51 and 64. Individuals that are 65 or older also have a lower probability of reporting to be in a higher health status compared to the individuals in the age group of 35-50 ($p<.001$). Interestingly, the direction of the coefficient for the year 2008 changed once age was included in the model. In Model 5, the probability of reporting to be in a higher health status was greater for individuals in 2008 relative to individuals in 2017 (4.3%, $p<.05$). In Model 6, the probability of being in a higher health status is about 8% lower in 2008 compared to 2017. The estimate of the variance component is much lower in Model 6 relative to the previous models, meaning that controlling for educational attainment, employment status, continent of origin, age, and type of immigrant destination explains a great portion of the variability in the dependent variable across metro areas.

We proceeded to conduct further analyses using 8 types of immigrant destinations rather than 3. In Table 4, we use major continuous gateways as the reference category as it contains the largest historical immigrant destinations in the US: Los Angeles, CA and New York-Northern New Jersey-Long Island, NY-NJ-PA. The results show that across all 5 models, the odds ratio of reporting to have a higher health status is greater for individuals in all new immigrant destinations (i.e., emerging, re-emerging, and pre-emerging) and low immigration destinations; however, the coefficients are not significant. Interestingly, the probability of reporting to have a higher health status for individuals in minor continuous gateways, which are smaller historical immigrant destinations, is lower compared to major continuous gateways. The coefficients for minor continuous gateways are negative and significant across all models. In Model 5, among all historical immigrant destinations included in the model, individuals in Post-World War II immigrant destinations have a higher probability of reporting to be in a higher health status compared to major continuous gateways, but the coefficient is not significant. In Model 6, the magnitude and significance of the coefficient for minor continuous gateways did not change greatly, but the magnitude and direction of low immigration and pre-emerging destinations decreased (not significant). The direction of re-emerging destinations changed, but it remained non-significant.

Minor continuous gateways are historical settlements of immigration but these have not experienced large influxes of immigrants in the same manner that major continuous gateways have. Additionally, the number of immigrants arriving to these regions has decreased in recent years. As the level of immigration continues to wane in historical immigrant destinations, first generation immigrants may have lower opportunities to form networks with other first-generation immigrants. The lack of resources and meaningful networks could also lead to an increase in mental health problems as well as an inability to seek medical help for other health issues.

Finally, we conducted binomial logistic regressions with self-reported health as the dichotomous outcome (not shown). We used a two-level binomial logistic general model with a random effect for metro areas (individuals nested in metro areas). Similar to the findings from the logistic ordinal regressions, the probability of reporting to have better health is statistically significant higher for immigrants in new destinations (OR=1.128, $p<.05$) and low-immigration destinations (OR=1.194, $p<.01$) compared to immigrants in historical immigrant destinations while controlling for continent of origin, educational attainment, employment status, age, and year. When we examine the differences in self-reported health across the 8 types of immigrant destinations, the probability of reporting to have better health is statistically significant higher for immigrants living in pre-emerging gateways (OR=1.353, $p<.05$), emerging gateways(OR=1.346, $p<.05$), and low-immigration destinations (OR=1.332, $p<.05$) compared to major continuous destinations. However, these differences become non-significant once we control for age.

Discussion

Despite the importance of community in shaping the health of the immigrant population in the United States, relatively little is known about what the changes in immigrant settlement patterns mean for the health of immigrants. Traditionally, the immigrant population has concentrated in major metropolitan areas, specifically Los Angeles, Chicago, and New York. However, new research suggests that immigrants have begun to diffuse across the United States, with certain metro areas now being classified as “new immigrant destinations”. This historic change in immigrant concentration has generated interests in trying to understand the social, economic, and health experiences of immigrants living in these new destinations.

Drawing on a large nationally representative sample of immigrants in the United States, we explore variation in health status among immigrants living in both traditional and non-traditional immigrant destinations. We find that immigrants living in non-traditional immigrant destinations (both new immigrant destinations and low immigration destinations) report better health than those immigrants living in historical immigrant destinations. This subjective health status difference remains after controlling for ethnicity, education, employment status, age, and year fixed effects.

Our results are surprising in several ways. First, drawing on the theoretical work of ethnic enclaves, we expected that immigrants would have better health in areas where immigrant communities were more established. Established immigrant communities are hypothesized to provide social and economic benefits to immigrants, as well as reduce potential acculturation stress. Given the abundance of this work, we expected that immigrants living in new and non-traditional areas would have worse health than their counter-parts living in historical destinations. We find that immigrants have better health in new immigrant destinations relative to historical immigrant destinations.

We hypothesized that this difference in health status between immigrant destinations might be driven by compositional differences in the immigrant population, as some research has shown that immigrants living in these newer destinations are different from immigrants in traditional destinations based on nationality, language proficiency, and age (Hall et al., 2011; Portes & Rumbaut, 2014). After adjusting our models to account for these compositional differences, we find that immigrants living in these non-traditional destinations still report better health.

The persistence of this health differential may have more implications for research concerning the health and well-being of immigrants in the United States. Whereas it was expected that immigrants living in areas surrounded by other immigrants (i.e., traditional immigrant destinations) would report better health, we find that immigrants in these areas reported worse health. This health differential might be the result of several potential different mechanisms. First, it is possible that while the concentration of immigrants in these traditional destinations provides immigrants with socially, culturally, and linguistically similar communities, these same communities also attract negative attention from law enforcement. It is possible that immigrants living in these traditional destinations, especially during this study period (2008-2017), experienced higher rates of stressful exposure with law enforcement. We believe that these traditional areas are easier targets for enforcement officers looking to carry out immigration laws. This may lead to increased scrutiny of all members of these communities, including both documented and undocumented migrants, the stress of which may be consequential to the health of all immigrants in these areas.

We are currently under contract with TRAC, a non-partisan organization that will provide us with data regarding immigration law enforcement at the county level, including rates and counts of apprehensions and deportations. We aim to use this new data to test if community variation in the enforcement of immigration law might explain community variation in immigrant health. We expect this data to be provided to us within the next two months (before December 2018).

The future plans for this project include the following:

1. Generate and explore trend data regarding the health of immigrants in these destination areas.

2. Further develop the conceptual framework to include more research about ethnic enclaves and immigrant health
3. Further develop the literature review to include more research about the social and economic experiences of immigrants in non-traditional destinations.
4. Construct and test our hypotheses regarding the role of immigration law enforcement in explaining community variation in immigrant health.

References

Acevedo-Garcia, D., Bates, L., Osypuk, T., & McArdle, N. (2010). The effect of immigrant generation and duration on self-rated health among US adults 2003-2007. *Social Science and Medicine*.

Akresh, I., & Frank, R. (2008). Health selection among new immigrants. *American Journal of Public Health*.

Allen, M., Elliott, M., Morales, L., Diamant, A., Hambarsoomian, K., & Schuster, M. (2007). Adolescent participation in preventive health behaviors, physical activity, and nutrition: Differences across immigrant generations for Asians and Latinos compared with whites. *American Journal of Public Health*.

Bean, F. D., Brown, S. K., Bachmeier, J. D., Brown, S., & Bachmeier, J. (2015). *Parents without papers: The progress and pitfalls of Mexican American integration*. Russell Sage Foundation.

Borjas, G. (1995). Ethnicity, Neighborhoods, and Human Capital Externalities.

Card, D. (2005). Is the new immigration really so bad? *Economic Journal*.

Department of Health Care Services. (2010). *Language access services for limited-English proficient and non-English proficient individuals.* Retrieved from: https://www.dhcs.ca.gov/services/medi-cal/eligibility/Documents/c10-03.pdf

Dreby, J. (2012). The Burden of Deportation on Children in Mexican Immigrant Families. *Journal of Marriage and Family*.

Durand, J., Massey, D. S., & Capoferro, C. (2005). The new geography of Mexican immigration. Hernández-León, R., & Zúñiga, V (eds.) *New destinations: Mexican immigration in the United States*. New York: Russell Sage Foundation.

Edin, P.-A., Fredriksson, P., & Aslund, O. (2003). Ethnic Enclaves and the Economic Success of Immigrants--Evidence from a Natural Experiment. *The Quarterly Journal of Economics*.

Eskelinen, L., Kohvakka, A., Merisalo, T., Hurri, H., & Wägar, G. (1991). *Relationship between the self-assessment and clinical assessment of health status and work ability.*

Ewing, W., Martínez, D., & Rumbaut, R. (n.d.). *The CriminalizaTion of immigraTion in The UniTed STaTeS.*

Fenelon, A. (2017). Rethinking the Hispanic Paradox: The Mortality Experience of Mexican Immigrants in Traditional Gateways and New Destinations. *International Migration Review*.

Hacker, K., Chu, J., Leung, C., Marra, R., Pirie, A., Brahimi, M., et al. (2011). The impact of Immigration and Customs Enforcement on immigrant health: Perceptions of immigrants in Everett, Massachusetts, USA. *Social Science and Medicine*.

Hall, M., Singer, A., De Jong, G. F., Graefe, D. R. (2011). The geography of immigrant skills: Educational profiles of metropolitan areas. *Metropolitan Policy Program at Brookings.*

Idler, E., & Benyamini, Y. (1997). *Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies.*

Ihlanfeldt, K., & Sjoquist, D. (1998). The Spatial Mismatch Hypothesis: A Review of Recent Studies and Their Implications for Welfare Reform. *Housing Policy Debate*.

Kain, J. (1968) Housing segregation, negro employment, and metropolitan decentralization, *Quarterly Journal of Economics, 82,* pp. 175– 197.

King, R., Massoglia, M., Uggen, C., Friedman, S., Galvan, C., McCarthy, J., et al. (2012). *Employment and Exile: U.S. Criminal Deportations, 1908-2005 1.*

Krause, N, & Jay, G. (1994). What do global self-rated health items measure? *Med Care*, 32. p. 930–942.

Lundberg, O., & Manderbacka, K. (1996). Assessing reliability of a measure of self-rated health. *Scandinavian journal of social medicine*, *24*(3), 218-224.

Marrow, H. (2005). New destinations and immigrant incorporation. *Perspectives on Politics, 3(4),* 781-799.

Medicaid. (2018). *Translation and interpretation services.* Retrieved from https://www.medicaid.gov/medicaid/finance/admin-claiming/translation/index.html

Neal, M., & Bohon, S. (2003). The dixie diaspora: Attitudes toward immigrants in Georgia. *Sociological Spectrum*.

Osypuk, T., Diez Roux, A., Hadley, C., & Kandula, N. (2009). Are immigrant enclaves healthy places to live? The Multi-ethnic Study of Atherosclerosis. *Social Science and Medicine*.

Pablos-Mendez A. Mortality among Hispanics. JAMA. (1994);271(16):1237. letter; comment on: JAMA 1993 Nov 24;270(20): 2464-8.

Pew Research Center. (2017). *Key Findings about U.S. Immigrants.* Retrieved from http://www.pewresearch.org/fact-tank/2017/05/03/key-findings-about-u-s-immigrants/

Pew Research Center. (2017). *Fact on US Immigrants, 2015.* Retrieved from: http://www.pewhispanic.org/2017/05/03/facts-on-u-s-immigrants/#fb-key-charts-age-pyramids

Portes, A., & Jensen, L. (1987). What's an ethnic enclave? The case for conceptual clarity. American Sociological Review, 52, 768–771.

Portes, A., & Jensen, L. (1989). The enclave and the entrants: Patterns of ethnic enterprise in Miami before and after Mariel. American Sociological Review, 54, 929–949.

Portes, A., & Jensen, L. (1992). Disproving the enclave hypothesis: Reply. American Sociological Review, 57, 418–420.

Portes, A., & Rumbaut, R. G. (2014). *Immigrant America: A portrait*.

Pumariega, A., Rothe, E., & Pumariega, J. (2005). Mental Health of Immigrants and Refugees. *Community Mental Health Journal*.

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. *Integrated Public Use Microdata Series, Current Population Survey: Version 6.0. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0*

TRAC. (2016). *Historical Data: Immigration and Customs Enforcement Removals.* Retrieved from: http://trac.syr.edu/phptools/immigration/removehistory/

Tran, T., Ma, G., Aroian, K., Balsam, A., & Conway, &. (2008). Living Arrangements, Depression, and Health Status Among Elderly Russian-Speaking Immigrants.

Turra, C., & Elo, I. (2008). The impact of salmon bias on the hispanic mortality advantage: New evidence from social security data. *Population Research and Policy Review*.

Xie, Y., & Gough, M. (2011). Ethnic Enclaves and the Earnings of Immigrants. *Demography*.

Appendix

Table 1: Distribution of individuals across 100 major metro areas in the US

Historical immigrant destinations	N	%	New immigrant destinations	N	%	Low immigration metros	N	%
Former gateways			Emerging gateways			Akron, OH	112	0.05%
Buffalo-Cheektowaga-Niagara Falls, NY	308	0.14%	Atlanta-Sandy Springs-Marietta, GA	3,830	1.80%	Albany-Schenectady-Troy, NY	243	0.11%
Cleveland-Elyria-Lorain-Mentor, OH	566	0.27%	Austin-Round Rock, TX	1,472	0.69%	Albuquerque, NM	1,242	0.58%
Detroit-Warren-Dearborn, MI	2,166	1.02%	Las Vegas-Paradise, NV	5,082	2.38%	Allentown-Bethlehem-Easton, PA-NJ	399	0.19%
Milwaukee-Waukesha-West Allis, WI	939	0.44%	Orlando, FL	2,411	1.13%	Augusta-Richmond County, GA-SC	91	0.04%
Pittsburgh, PA	419	0.20%	Phoenix-Mesa-Scottsdale, AZ	3,110	1.46%	Baton Rouge, LA	204	0.10%
Providence-Fall River-Warwick, RI-MA	3,774	1.77%	Re-emerging gateways			Birmingham-Hoover, AL	250	0.12%
St. Louis. MO-IL	632	0.30%	Baltimore-Columbia-Towson, MD	2,355	1.10%	Boise City-Nampa, ID	824	0.39%
Post-World War II gateways			Denver-Aurora-Lakewood, CO	2,479	1.16%	Sarasota-Bradenton-Venice, FL	396	0.19%
Dallas-Forst Worth-Arlington, TX	6,394	3.00%	Minneapolis-St Paul-Bloomington, MN-WI	2,826	1.33%	Charleston-North Charleston, SC	239	0.11%
Houston-Baytown-Sugar Land, TX	6,670	3.13%	Philadelphia-Camden-Wilmington, PA-NJ-DE	5,100	2.39%	Chattanooga, TN-GA	204	0.10%
Los Angeles, CA	25,046	11.75%	Portland-Vancouver-Hillsboro, OR-WA	2,198	1.03%	Cincinnati, OH-KY-IN	524	0.25%
Miami-Fort Lauderdale-West Palm Beach, FL	11,858	5.56%	Sacramento-Arden Arcade-Roseville, CA	2,112	0.99%	Colorado Springs, CO	472	0.22%
Riverside-San Bernardino-Ontario, CA	4,839	2.27%	San Jose-Sunnyvale-Santa Clara, CA	3,531	1.66%	Columbia, SC	278	0.13%
San Diego-Carlsbad-San Marcos, CA	3,830	1.80%	Seattle-Tacoma-Bellevue, WA	3,329	1.56%	Dayton, OH	143	0.07%
Washington,DC-MD-VA-WV	12,735	5.97%	Tampa-St. Petersburg-Clearwater, FL	1,986	0.93%	Des Moines, IA	597	0.28%
Major-Continuous gateways			Pre-emerging gateways			Grand Repids-Wyoming, MI	294	0.14%
Boston-Cambridge-Quincy, MA-NH	3,458	1.62%	Cape Coral-Fort Myers, FL	540	0.25%	Greenville-Mauldin-Easley, SC	298	0.14%
Chicago-Naperville-Joliet, IL-IN-WI	8,525	4.00%	Charlotte-Gastonia-Concord, NC-SC	1,125	0.53%	Harrisburg-Carlisle, PA	186	0.09%
New York-Northern New Jersey-Long Island, NY-NJ-PA	27,988	13.13%	Columbus, OH	627	0.29%	Indianapolis-Carmel, IN	637	0.30%
San Francisco-Oakland-Fremont, CA	6,718	3.15%	Greensboro-High Point, NC	353	0.17%	Jackson, MS	177	0.08%
Minor-continuous gateways			Lakeland-Winter Haven, FL	287	0.13%	Jacksonville, FL	558	0.26%
Bakersfield, CA	1,061	0.50%	Nashville-Davidson-Murfreesboro, TN	590	0.28%	Kansas City, MO-KS	1,139	0.53%
Bridgeport-Stamford-Norwalk, CT	1,882	0.88%	Raleigh-Carey, NC	864	0.41%	Knoxville, TN	157	0.07%
El Paso, TX	1,305	0.61%	Salt Lake City, UT	1,356	0.64%	Little Rosk-North Little Rock, AR	316	0.15%
Fresno, CA	1,056	0.50%				Louisville, KY-IN	430	0.20%
Harford-West-Harford-East, CT	1,857	0.87%				Madison, WI	253	0.12%
Honolulu, HI	5,206	2.44%				Memphis, TN-AR-MS	454	0.21%
McAllen-Edinburg-Pharr, TX	1,216	0.57%				New Orleands-Metairie, LA	584	0.27%
Modesto, CA	628	0.29%				Ogden-Clearfield, UT	414	0.19%
New Haven-Milford, CT	1,079	0.51%				Oklahoma City, OK	730	0.34%
Oxnard-Thousand Oaks-Ventura, CA	1,150	0.54%				Omaha-Council Bluffs, NE-IA	1,074	0.50%
Rochester, NY	353	0.17%				Palm Bay-Melbourne-Titusville, FL	252	0.12%
San Antonio, TX	1,427	0.67%				Portland-South Portland, ME	423	0.20%
Stockton, CA	924	0.43%				Poughkeepsie-Newburgh-Middletown	288	0.14%
Tucson, AZ	861	0.40%				Provo-Orem, UT	378	0.18%
Worcester, MA-CT	471	0.22%				Richmond, VA	530	0.25%
						Scranton-Wilkes-Barre, PA	157	0.07%
						Springfield, MA-CT	462	0.22%
						Syracuse, NY	196	0.09%
						Toledo, OH	97	0.05%
						Tulsa, OK	410	0.19%
						Virginia Beach-Norfolk-Newport News, VA-NC	551	0.26%
						Wichita, KS	562	0.26%
						Youngstown-Warren-Boardman, OH-PA	63	0.03%
Total for each type of destination:	147,341			47,563			18,288	
Total number of individuals across all metro areas:							213,192	100%

Table A1: Distribituion of individual across the three types of immigrant destinations		
	N	%
Historical immigrant destinations	147,341	69.11%
Former gateways	8,804	
Post-World War II gateways	71,372	
Major-Continuous gateways	46,689	
Minor-continuous gateways	20,476	
New immigrant destinations	47,563	22.31%
Emerging gateways	15,905	
Re-emerging gateways	25,916	
Pre-emerging gateways	5,742	
Low immigration metros	18,288	8.58%
Total:	213,192	100.00%

Table 2: Descriptive statistics

		Frequency	Percentage
Self-rated health			
	Poor	7,286	3.418%
	Fair	20,726	9.722%
	Good	65,141	30.560%
	Very good	65,473	30.710%
	Excellent	54,566	25.590%
Immigrant destinations			
	Former gateway	8,804	4.130%
	Post-World War II gateway	71,372	33.478%
	Emerging gateway	15,905	7.460%
	Major-continuous gateway	46,689	21.900%
	Re-emerging gateway	25,916	12.156%
	Minor-continuous gateway	20,476	9.604%
	Pre-emerging gateway	5,742	2.693%
	Low immigration gateway	18,288	8.578%
Continent of origin			
	Oceania	1,364	0.640%
	Africa	9,287	4.356%
	Asia	60,437	28.349%
	Europe	20,082	9.420%
	South America	14,464	6.784%
	Center America	104,647	49.086%
	North America	2,911	1.365%

Table 2: Descriptive statistics

		Frequency	Percentage
Educational attainment			
	Less than high school education	63,321	29.701%
	High school education	53,382	25.039%
	Some college	37,394	17.540%
	Bachelor's degree or higher	59,095	27.719%
Employment status			
	Employed	131,628	61.742%
	Unemployed	81,564	38.258%
Age			
	0 to 18	7,230	3.39%
	19 to 35	60,457	28.36%
	35 to 50	73,672	34.56%
	51 to 64	44,079	20.68%
	65 and above	27,754	13.02%
Year			
	2008	20,964	9.829%
	2009	21,077	9.882%
	2010	21,809	10.225%
	2011	21,985	10.307%
	2012	22,092	10.358%
	2013	22,203	10.410%
	2014	22,187	10.402%
	2015	21,678	10.164%
	2016	19,270	9.035%
	2017	19,927	9.343%
Total number of metro areas		100	
Individuals		213,192	

Table 3: Multilevel ordinal logistic regression of health status

	Model 1	Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	Coef.	OR	Coef.	OR	Coef.	OR	Coef.	OR	Coef.	OR
	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err)	(Std. Err.)	(Std. Err.)
Immigrant destinations or gateways (Reference: Historical immigrant destination)											
New immigrant destination		0.231***	1.260***	0.220***	1.246***	0.211***	1.235***	0.189***	1.208***	0.111*	1.117*
		(0.063)	(0.079)	(0.058)	(0.072)	(0.056)	(0.069)	(0.052)	(0.062)	(0.049)	(0.055)
Low immigrant destination		0.263***	1.301***	0.239***	1.269***	0.237***	1.267***	0.219***	1.245***	0.123**	1.131**
		(0.054)	(0.070)	(0.050)	(0.063)	(0.048)	(0.061)	(0.045)	(0.056)	(0.043)	(0.049)
Continent (Reference: Center America)											
Oceania				0.494***	1.639***	0.242***	1.274***	0.313***	1.368***	0.221***	1.247***
				(0.050)	(0.082)	(0.050)	(0.064)	(0.051)	(0.069)	(0.051)	(0.064)
Africa				0.437***	1.547***	0.163***	1.177***	0.212***	1.236***	0.211***	1.235***
				(0.020)	(0.031)	(0.021)	(0.024)	(0.021)	(0.026)	(0.021)	(0.026)
Asia				0.280***	1.323***	-0.0546***	0.947***	0.022*	1.023*	0.126***	1.134***
				(0.010)	(0.013)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.013)
Europe				0.311***	1.364***	-0.002	0.998	0.080***	1.083***	0.312***	1.366***
				(0.015)	(0.020)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.021)
South America				0.369***	1.447***	0.158***	1.171***	0.176***	1.192***	0.224***	1.251***
				(0.017)	(0.024)	(0.017)	(0.020)	(0.017)	(0.020)	(0.017)	(0.021)
North America				0.722***	2.059***	0.371***	1.449***	0.466***	1.593***	0.722***	2.058***
				(0.035)	(0.071)	(0.035)	(0.051)	(0.035)	(0.056)	(0.036)	(0.074)
Educational attainment (Reference: No high school education)											
High school education						0.295***	1.343***	0.199***	1.220***	0.285***	1.330***
						(0.011)	(0.015)	(0.011)	(0.013)	(0.011)	(0.015)
Some college						0.604***	1.829***	0.479***	1.615***	0.483***	1.620***
						(0.012)	(0.023)	(0.013)	(0.020)	(0.013)	(0.021)
Bachelor's degree or higher						0.865***	2.374***	0.679***	1.972***	0.777***	2.175***
						(0.012)	(0.028)	(0.012)	(0.024)	(0.013)	(0.027)
Employment status (Reference: Unemployed)											
Employed								0.696***	2.006***	0.548***	1.730***
								(0.009)	(0.017)	(0.009)	(0.016)
Age (Reference: 35 to 50)											
0 to 18										1.466***	4.332***
										(0.024)	(0.106)
19 to 35										0.474***	1.606***
										(0.010)	(0.016)
51 to 64										-0.617***	0.540***
										(0.011)	(0.006)
65 and above										-1.237***	0.290***
										(0.015)	(0.004)
Year (Reference: 2017)											
2008		0.010	1.010	0.019	1.019	0.060**	1.062**	0.042*	1.043*	-0.0880***	0.916***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)
2009		-0.077***	0.926***	-0.071***	0.931***	-0.037*	0.964*	-0.039*	0.961*	-0.157***	0.855***
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2010		-0.101***	0.903***	-0.092***	0.912***	-0.057**	0.944**	-0.053**	0.949**	-0.160***	0.852***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.015)
2011		-0.058**	0.944**	-0.052**	0.950**	-0.015	0.985	-0.006	0.994	-0.0921***	0.912***
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
2012		-0.094***	0.910***	-0.093***	0.912***	-0.065***	0.937***	-0.058**	0.944**	-0.127***	0.881***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2013		-0.075***	0.928***	-0.071***	0.931***	-0.052**	0.950**	-0.043*	0.958*	-0.105***	0.900***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2014		-0.031	0.97	-0.026	0.975	-0.003	0.997	0.003	1.003	-0.0426*	0.958*
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
2015		-0.052**	0.949**	-0.049**	0.952**	-0.033	0.968	-0.030	0.970	-0.055**	0.946**
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
2016		-0.002	0.998	-0.001	0.999	0.007	1.007	0.011	1.011	0.00532	1.005
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Threshold 1	-3.426[a]	-3.311[a]		-3.156[a]		-3.038[a]		-2.720[a]		-3.001[a]	
	(0.029)	(0.043)		(0.040)		(0.092)		(0.085)		(0.037)	
Threshold 2	-1.968[a]	-1.853[a]		-1.695[a]		-2.566[a]		-1.223[a]		-1.428[a]	
	(0.027)	(0.042)		(0.039)		(0.091)		(0.085)		(0.036)	
Thershold 3	-0.313[a]	-0.197[a]		-0.032		0.128[a]		0.513[a]		0.456[a]	
	(0.027)	(0.042)		(0.039)		(0.091)		(0.085)		(0.035)	
Threshold 4	1.026[a]	1.142[a]		1.316[a]		1.501[a]		1.908[a]		1.943[a]	
	(0.027)	(0.042)		(0.039)		(0.091)		(0.085)		(0.036)	
τ_{00}	0.065[a]	0.049[a]		0.041[a]		0.032[a]		0.027[a]		0.023[a]	
	(0.010)	(0.008)		(0.007)		(0.006)		(0.005)		(0.005)	
Chi-squared		120.91***		1871.61***		7561.92***		14079.57***		34686.89	
Log-likelihood	-300062.55	-300003.75		-299127.17		-296238.11		-292846.20		-281577	
Observations	213192	213192	213192	213192	213192	213192	213192	213192	213192	213192	
Number of groups	100	100	100	100	100	100	100	100	100	100	

*** p<0.01, ** p<0.05, * p<0.1, [a]Significant based on confidence interval

Table 4: Multilevel ordinal logistic regression of health status

	Model 1	Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	Coef.	OR	Coef.	OR	Coef.	OR	Coef.	OR	Coef.	OR
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
Immigrant destinations or gateways (Reference: Major continuous gateways)											
Former		-0.0828	0.921	-0.124	0.884	-0.103	0.902	-0.0881	0.916	-0.186	0.830
		(0.131)	(0.120)	(0.118)	(0.104)	(0.116)	(0.104)	(0.107)	(0.098)	(0.100)	(0.083)
Post-World War II		-0.065	0.937	0.008	1.008	0.013	1.013	0.011	1.011	0.0115	1.012
		(0.128)	(0.120)	(0.115)	(0.116)	(0.113)	(0.114)	(0.104)	(0.105)	(0.097)	(0.098)
Emerging		0.103	1.109	0.165	1.179	0.175	1.191	0.175	1.191	0.106	1.112
		(0.138)	(0.153)	(0.124)	(0.146)	(0.121)	(0.145)	(0.112)	(0.134)	(0.104)	(0.116)
Re-emerging		0.0125	1.013	-0.0003	1.000	0.0149	1.015	0.00519	1.005	-0.0881	0.916
		(0.124)	(0.125)	(0.111)	(0.111)	(0.109)	(0.110)	(0.100)	(0.101)	(0.093)	(0.085)
Minor-continuous		-0.323**	0.724**	-0.266*	0.766*	-0.220*	0.803*	-0.196*	0.822*	-0.195*	0.823*
		(0.116)	(0.084)	(0.105)	(0.080)	(0.102)	(0.082)	(0.095)	(0.078)	(0.088)	(0.072)
Pre-emerging		0.0764	1.079	0.116	1.123	0.14	1.15	0.128	1.137	0.00748	1.008
		(0.128)	(0.138)	(0.116)	(0.130)	(0.113)	(0.130)	(0.105)	(0.119)	(0.098)	(0.099)
Low immigration		0.0882	1.092	0.0975	1.102	0.122	1.13	0.118	1.125	0.00275	1.003
		(0.108)	(0.118)	(0.097)	(0.107)	(0.095)	(0.107)	(0.088)	(0.099)	(0.082)	(0.082)
Continent (Reference: Center America)											
Oceania				0.495***	1.640***	0.243***	1.275***	0.314***	1.369***	0.222***	1.249***
				(0.050)	(0.082)	(0.050)	(0.064)	(0.051)	(0.069)	(0.051)	(0.064)
Africa				0.437***	1.548***	0.164***	1.178***	0.212***	1.237***	0.212***	1.237***
				(0.020)	(0.031)	(0.021)	(0.024)	(0.021)	(0.026)	(0.021)	(0.026)
Asia				0.280***	1.324***	-0.0542***	0.947***	0.0227*	1.023*	0.126***	1.135***
				(0.010)	(0.013)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.013)
Europe				0.311***	1.365***	-0.001	0.999	0.080***	1.083***	0.313***	1.367***
				(0.015)	(0.020)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.021)
South America				0.369***	1.447***	0.158***	1.171***	0.176***	1.192***	0.224***	1.251***
				(0.017)	(0.024)	(0.017)	(0.020)	(0.017)	(0.020)	(0.017)	(0.021)
North America				0.723***	2.060***	0.371***	1.450***	0.466***	1.594***	0.723***	2.060***
				(0.035)	(0.072)	(0.035)	(0.051)	(0.035)	(0.056)	(0.036)	(0.074)
Educational attainment (Reference: No high school education)											
High school education						0.295***	1.343***	0.199***	1.220***	0.285***	1.330***
						(0.011)	(0.015)	(0.011)	(0.013)	(0.011)	(0.015)
Some college						0.604***	1.829***	0.479***	1.615***	0.483***	1.620***
						(0.012)	(0.023)	(0.013)	(0.020)	(0.013)	(0.021)
Bachelor's degree or higher						0.865***	2.374***	0.679***	1.972***	0.777***	2.175***
						(0.012)	(0.028)	(0.012)	(0.024)	(0.013)	(0.027)
Employment status (Reference: Unemployed)											
Employed								0.696***	2.006***	0.548***	1.730***
								(0.009)	(0.017)	(0.009)	(0.016)
Age (Reference: 35 to 50)											
0 to 18										1.466***	4.333***
										(0.024)	(0.106)
19 to 35										0.474***	1.607***
										(0.010)	(0.016)
51 to 64										-0.617***	0.540***
										(0.011)	(0.006)
65 and above										-1.237***	0.290***
										(0.015)	(0.004)
Year (Reference: 2017)											
2008		0.00963	1.010	0.0186	1.019	0.0602**	1.062**	0.0420*	1.043*	-0.0879***	0.916***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)
2009		-0.0768***	0.926***	-0.0710***	0.931***	-0.0371*	0.964*	-0.039*	0.961*	-0.157***	0.855***
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2010		-0.101***	0.903***	-0.0916***	0.913***	-0.0572**	0.944**	-0.052**	0.949**	-0.160***	0.852***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.015)
2011		-0.0581***	0.944***	-0.0515**	0.950**	-0.015	0.985	-0.00607	0.994	-0.0920***	0.912***
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
2012		-0.0942***	0.910***	-0.0925***	0.912***	-0.0651***	0.937***	-0.058**	0.944**	-0.127***	0.881***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2013		-0.0746***	0.928***	-0.0711***	0.931***	-0.0516**	0.950**	-0.043*	0.958*	-0.105***	0.900***
		(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)
2014		-0.0314*	0.969*	-0.0256	0.975	-0.00299	0.997	0.00266	1.003	-0.043	0.958
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
2015		-0.0522***	0.949***	-0.0488***	0.952***	-0.033	0.968	-0.030	0.970	-0.055**	0.946**
		(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
2016		-0.002	0.998	-0.001	0.999	0.007	1.007	0.011	1.011	0.00525	1.005
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Threshold 1	-3.426[a]	-3.486[a]		-3.297[a]		-3.038[a]		-2.720[a]		-3.121[a]	
	(0.029)	(0.104)		(0.094)		(0.092)		(0.085)		(0.080)	
Threshold 2	-1.968[a]	-2.028[a]		-1.837[a]		-1.566[a]		-1.223[a]		-1.548[a]	
	(0.027)	(0.104)		(0.093)		(0.091)		(0.085)		(0.079)	
Threshold 3	-0.313	-0.372[a]		-0.173		0.128		0.513[a]		0.336[a]	
	(0.027)	(0.103)		(0.093)		(0.091)		(0.085)		(0.079)	
Threshold 4	1.026[a]	0.967[a]		1.175[a]		1.501[a]		1.908[a]		1.8223[a]	
	(0.027)	(0.103)		(0.093)		(0.093)		(0.085)		(0.079)	
Variance component	0.065[a]	0.042[a]		0.033[a]		0.032[a]		0.027[a]		0.023[a]	
	(0.010)	(0.007)		(0.006)		(0.006)		(0.005)		(0.004)	
Chi-squared		139.54***		1896.74***		7561.92***		14079.57***		34045.14***	
Log-likelihood	300062.55	299997.20		299119.79		296238.11		292846.20		278302.40	
Observations	213,192	213,192	213,192	213,192	213,192	213,192	213,192	213,192	213,192	213,192	213,192
Number of groups	100	100	100	100	100	100	100	100	100	100	100

*** p<0.001, ** p<0.01, * p<0.05 [a]Significant based on confidence interval