Beyond Typologies: A Multilevel Approach to Understanding the Impact of Destinations on Immigrant Outcomes.

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Abstract

Immigrant destination typologies are increasingly used to compare immigrant outcomes across geographic areas within the United States. Results from analyses that use destination typologies, however, are sensitive to the choice of criteria that defines destination types, as well as to variations in the geographic unit of analysis. Destination categories may also mask important sources of intra-destination variation. I argue that the study of immigrant destinations could benefit from the use of multilevel modeling. Multilevel models allow researchers to examine how the characteristics of destinations and the individuals within them produce variations in outcomes across immigrant-receiving areas. To demonstrate the utility of this approach, I use the 2005-2009 American Community Survey to examine patterns of school non-enrollment among Mexican origin 15-17 year-olds across U.S. states. My models assess how individual and state-level factors produce between-state variation in the likelihood of Mexican origin non-enrollment. I argue that this modeling technique can inform the future study of immigrant outcomes across destinations.

Introduction

What is a "new" immigrant destination? Researchers who study new immigrant destinations often conceptualize these places in a similar way, as locations that had a negligible foreign-born presence prior to the 1990s and experienced significant growth in the immigrant population thereafter. Despite this conceptual congruence, most studies of new immigrant destinations define the boundaries of new and other types of destinations differently. For instance, Singer (2004, 2008) creates a six-category destination typology for metropolitan areas that takes into account an area's historical experience as an immigrant destination, as well as recent and projected foreign-born growth rates. Her typology includes former gateways (places that received earlier waves of migrants but are no longer immigrant destinations), continuous gateways (places that have continuously received immigrants, such as New York and Chicago), Post-World War II gateways (places that became immigrant destinations after World War II), emerging gateways (places that have experienced rapid immigration in the past 25 years), re-emerging gateways (places that were major immigrant destinations in the early 20th century, followed by a hiatus in the middle of the century, and a resurgence in recent decades) , and pre-emerging gateways (places that experienced rapid growth in the foreign-born population in the1990s, and are poised to experience further growth in the future). In contrast, other studies distinguish new from established and other types of destinations based on two factors: 1) the proportion of immigrants living in a given geographic unit of analysis in a baseline year; and 2) the rate of growth in the foreign-born population in the geographic unit of analysis between the baseline year and a subsequent time period (see Fischer 2010; Lichter et al. 2010; Park and Iceland 2011).

The diversity of destination typologies in the current literature on new immigrant destinations poses a number of challenges for researchers seeking to generalize findings across studies. First, the number of destination categories typically varies across studies. Second, researchers often use a different set of criteria to define a geographic area as a new destination. As a result, the proportion of the total ethno-racial population that is reported to be living in new destinations differs across studies. This has important implications for study findings, and may be one reason why studies researching the same social phenomenon reach divergent conclusions (see, for example, Fischer and Tienda 2006, Lichter et al. 2010, and Park and Iceland 2011, on segregation levels in new destinations). Finally, destination typologies may mask intra-destination heterogeneity. By design, destination typologies categorize geographic areas together based on a common immigration history. The literature on immigrant destinations, however, reveals substantial heterogeneity among places that are commonly considered to be new destinations. The "new destinations" label may thus obscure other contextual factors that drive inter-place variation in outcomes that are used to measure immigrant incorporation.

As researchers move forward in the study of immigrant incorporation across destinations, it will become increasingly important to acknowledge the limitations of destination typologies. I argue that the field should pay greater attention to identifying the specific contextual factors that shape common or divergent outcomes among immigrants across destinations. These factors may include variables related to a destination's immigration history, but could also include other contextual factors that previous research has shown to be relevant to the outcome of interest. I posit that the literature on new destinations would benefit from the use of multilevel statistical models.

Multilevel modeling provides an understanding of how individual, household, and external factors work together to create between-destination variations in the outcome of interest. The use of multilevel modeling would allow researchers to identify the variables that generate heterogeneity in outcomes across destinations, while remaining agnostic about defining destinations as “new” or “established.”

In this paper, I demonstrate the utility of a multilevel approach to understanding between-place heterogeneity in immigrant outcomes, by examining variations in the likelihood of school non-enrollment among Mexican origin 15-17 year-olds[1] across U.S. states. I use individual and household data from the 2005-2009 American Community Survey (ACS) to construct several individual-level (level 1) variables that may influence patterns of non-enrollment across states. In addition, I use a 1990 decennial census 5% microdata sample, the 2005-2009 ACS, and the 2010 ACS to create three types of state-level (level 2) variables that may explain variations in Mexican origin non-enrollment across states: immigration history, peer composition, and educational context.

I find considerable variation in Mexican origin non-enrollment rates across states. Compositional factors, particularly immigrant generational status, play a major role in explaining between-state variance in the likelihood of non-enrolment. Surprisingly, immigration history variables that are commonly used in destination typologies (the percent foreign born in the state in 1990 and percent foreign-born growth rates from 1990 to 2010) have a negligible influence on between-state variation in the likelihood of Mexican origin non-enrollment. Additionally, these variables do not have significant effects on the log odds of Mexican origin non-enrollment, net of compositional factors.

[1] I refer to 15-17 year-olds as “adolescents” throughout this analysis.

In contrast, variables related to the context of education in the state, particularly the percent of non-Hispanic White 15-17 year-olds who are not enrolled in school, reduce between-state variation in Mexican origin non-enrollment. The likelihood of non-enrollment also increases significantly as the percent of non-enrolled NH Whites in the state increases, net of the compositional factors. These results suggest that researchers should proceed with caution when assuming that immigration history plays an all-important role in shaping heterogeneous outcomes across destinations.

Background

Prior to the 1990s, immigrant settlement in the United States followed a predictable geographic pattern, with the majority of immigrants settling in urban areas in a handful of immigrant-receiving states. Portes and Rumbaut (2006) note that this consistent spatial pattern was largely the result of the "characteristic economics of immigration," in which immigrants were drawn by co-ethnic recruitment into entry level or low-skilled jobs in urban areas undergoing economic growth (58-59). This pattern began to shift in the last decades of the 20th century, with increasing numbers of immigrants settling outside of established gateways, in "new destinations" such as Marshalltown, Iowa and Dalton, Georgia (Zúñiga and Hernández-León 2005). A number of factors have helped to "push" immigrant origin populations out of established gateways and "pull" them into new destinations, including comprehensive immigration reform in the 1980s, nativist hostility in established gateways such as California, border control policies that have inadvertently increased immigrant settlement by raising the cost of circular migration, and industrial relocation and restructuring in sectors that involve manual labor, such as meatpacking (Massey and Capoferro 2008; Parrado and Kandel 2008).

Mexican origin immigrants account for a sizeable proportion of the foreign-born population living in non-established destinations. In 2005, approximately 30 percent of all recent Mexican immigrant arrivals (individuals who entered the country in the previous five years) were living outside of the “Big Five” states of immigration (California, Texas, Florida, Illinois, New York), nearly double the percentage of Mexican origin new arrivals that resided outside of these states in 1990 (Massey and Capoferro 2008: 40). Recent immigrant arrivals from other regions, including Asia and Other (non-Mexican) Latin American countries have also been drawn into areas outside of the Big Five established gateway states (Massey and Capoferro 2008).

The emergence of new immigrant destinations has coincided with a proliferation of studies that seek to incorporate new destinations into the broader fold of theories of immigration and assimilation. I conceptualize the previous research on immigrants in new destinations as proceeding in two waves.[2] The first wave of research focused on describing the emergence of new destinations and generating explanations for these changing patterns of immigrant settlement. In addition, studies in the first phase of research sought to understand the dynamics of incorporation for immigrants in new destinations by addressing such questions as “who immigrates to new destinations?” and “how are these immigrants received?” Studies in two edited volumes, Zúñiga and Hernández-León’s *New Destinations: Mexican Immigration in the United States* (2005) and Douglas Massey’s *New Faces in New Places* (2008), typify this wave of research.

[2] These waves of research are not necessarily chronologically distinct. In dividing the previous research on new destinations into these two waves, I seek to highlight differences in content and methodological approach, rather than differences in timing.

These volumes include both quantitative and qualitative studies, with many studies taking a localized approach to understanding immigrant destinations. To be sure, most of the research in these two volumes focuses on specific new destination communities, such as Marshalltown, Iowa (Grey and Woodrick 2008) or particular new destination industries such as meatpacking and construction (Parrado and Kandel 2008).

Importantly, the first wave of research on new destinations has shown that, compared to established urban immigrant gateways, new destinations are extremely diverse. New destinations include suburban areas (Hardwick 2008), nonmetropolitan "offset" counties—places where the immigrant population has offset the decline of the native-born population (Donato et al. 2008), and nonmetropolitan areas that were previously dominated by non-Hispanic whites (Kandel and Cromartie 2004). In addition, urban places that have been historical gateways for some immigrant groups have become new destinations for others. For instance, Mexican origin immigrants have recently begun to settle in New York City (Smith 2006), a quintessential established immigrant gateway.

The second wave of research on immigrants in new destinations is largely comparative and inferential. In this phase of inquiry, researchers often use large, nationally representative datasets and multivariate analysis to compare immigrant outcomes across new versus other types of destinations, and examine the determinants of these variations. This wave of research is partly a response to Waters and Jiménez's (2005) call for new destinations to be integrated into theories of immigrant assimilation. Many studies in this phase of research compare outcomes related to immigrant asimilation, such as segregation (Fischer and Tienda 2006; Lichter et al. 2010; Park and

Iceland 2011) and school non-enrollment (Fischer 2010), across destinations. This wave of research is particularly concerned with determining whether new destinations contribute positively or negatively to immigrant outcomes compared to other types of destinations, net of compositional factors. For instance, a recent study by Fischer (2010) compares school non-enrollment rates among 15-17 year-old across four types of destinations (new, established maintaining, established growing, and non-destinations), and assesses whether these differences persist when compositional factors related to social origins are taken into account. She finds that the likelihood of non-enrollment is persistently higher for 15-17 year-olds in new destinations than in established maintaining destinations, net of compositional factors.

This wave of research is dominated by the use of destination typologies that use a given set of criteria to define the boundaries of new versus other types of destinations. As discussed, many researchers conceptualize new destinations similarly, viewing them as places that had a negligible foreign-born presence prior to a baseline time period and experienced rapid foreign-born growth thereafter. In practice, however, researchers do not measure new destinations in the same way. The number of destination categories within a typology may vary across studies. For instance, while Singer (2004) uses a six-category typology to describe the immigration history of metropolitan areas, a recent study of non-enrollment across destinations (Fischer 2010) uses four categories (new destinations, established growing destinations, establishing maintaining destinations), and two other recent studies of segregation across destinations (Lichter et al. 2010; Park and Iceland 2011) use three categories (new destinations, established destinations, and "other" types of destinations).

Studies that use a similar number of destination categories may also measure destinations differently. To provide an example, I compare the destination typologies used in three recent studies of differences in Hispanic segregation levels across destinations in 1990 and 2000 (Fischer and Tienda 2006; Lichter et al. 2010; Park and Iceland 2011).[3] Fischer and Tienda (2006) analyze the top 100 metropolitan areas, and divide these areas into three categories: Traditional metros, new Hispanic destinations, and other large metros. Traditional metros are defined as the 29 metro areas in the Southwestern states (Texas, New Mexico, Colorado, Arizona, and California) and the established gateway cities of Miami, New York City (including Newark, NJ), and Chicago. New Hispanic destinations include 50 metropolitan areas that cannot be defined as traditional metros and where the Hispanic population increased "appreciably" from 1980 to 2000 (2006:103). Fischer and Tienda do not provide a clear cut-off point to distinguish new Hispanic destinations from other large metros, but note that the percent foreign-born within new Hispanic destinations doubled, from 6 to 12 percent, from 1980 to 2000. Other large metros include the remaining 21 metropolitan areas that had less than a 5 percent Hispanic population in all years of the analysis (1980, 1990, 2000).

Similar to Fischer and Tienda, Park and Iceland (2011) limit their analysis to the top 150 metropolitan areas. Park and Iceland seek to consolidate Singer's (2004, 2008) typology into three categories: Established gateways, new destinations, and other gateways. They define established gateways as places where the proportion of foreign-born individuals within the metropolitan area was greater than the national average proportion of foreign-born individuals for each decade of the 20th century, or where the

[3] Fischer and Tienda (2006) also examine segregation patterns in 1980.

proportion of foreign-born individuals exceeded the national average after World War II. New destinations are defined as non-established gateways that had small foreign-born populations prior to1970 and growing foreign-born proportions after 1980. Similar to Fischer and Tienda (2006), Park and Iceland do not provide a clear cut-off point for distinguishing new destinations from other gateways. Other gateways are considered metropolitan areas that cannot be defined as either established gateways or new destinations.

In contrast to Fischer and Tienda, and Park and Iceland, Lichter et al. (2010) define destinations at a lower level of geography-- the "place" level. The universe of places includes metro central cities, metro suburban places, and non-metropolitan places (n=21,093). An advantage to this approach is that it includes non-metropolitan areas, which account for some of the growth of new immigrant destinations (Kandel and Cromartie 2004). Lichter et al. do not use data on the size and growth of the total foreign-born population to categorize destinations, but focus exclusively on the size and growth of the Hispanic population. Established places are defined as places where Hispanics represented 18 percent or more of total population in 1990 (double the overall proportion of Hispanic individuals living in the U.S. in 1990). Places must meet three criteria to be defined as new destinations: 1) The proportion of Hispanics living in the place had to be lower than the national average in 1990 (9 percent); 2) The total Hispanic population had to have grown by at least 200 individuals from 1990 to 2000; 3) The Hispanic growth rate from 1990 to 2000 had to exceed the national average by one standard deviation. "Other" Hispanic places are those that cannot be considered established places or new destinations.

Inconsistencies in the geographic unit of analysis and the criteria used to define destinations in these three studies make it difficult to compare findings across studies. In addition, variations in the measurement of new, established, and "other" destinations imply that different proportions of the Hispanic population are reported to be living in places that are considered to be new destinations. In Fischer and Tienda's (2006) analysis, for example, approximately 16 percent of all Hispanics living in metropolitan areas are living in new destinations, whereas Park and Iceland (2011) report that 26.4 percent of all Hispanics are living in new destinations. In Lichter et al.'s (2010) analysis, only 1.2 percent of all Hispanics in 2000 were living in places they define as new destinations. As a result, each of these analyses is referring to different subgroups within the Hispanic population using the same nomenclature— "new destinations."

Variations in destination typologies may also help to explain why these studies reach divergent conclusions. Lichter et al. (2010) find that Hispanic-white segregation is higher in new destination places than in established destination places, whereas Fischer and Tienda (2006) and Park and Iceland (2011) find that Hispanic-white segregation in metro new destinations is generally lower than in established metros. These conflicting results could also be due to variations in the geographic unit of analysis. Findings from studies that use distinct destination typologies will thus always be sensitive to both the geographic unit of analysis and the criteria used to distinguish new from established and other types of destinations.

Beyond measurement concerns, an over-reliance on destination typologies could overshadow intra-destination heterogeneity. By design, destination typologies emphasize between-group differences (new versus established destinations) rather than within-group differences (intra-group variation in new destinations, for example). As discussed, new destinations are diverse on several measures, including metropolitan status and the types of populations that lived in the destination prior to the arrival of immigrants. Current studies are beginning to quantify this variation. In their analysis of segregation patterns across destinations, for example, Fischer and Tienda (2006) note that the average level of segregation for the entire population of new destination metropolitan areas masks substantial variation in segregation levels across new destination metros. They attribute this variation to differences in size, pre-existing minority populations, and the timing of the arrival of Hispanics.

A destination's immigration history may not be a major determinant of certain outcomes related to immigrant assimilation. For instance, the factors that shape segregation in Atlanta, Georgia, may not be the same as those that influence segregation in Lincoln, Nebraska, despite the fact that these areas are both considered new destinations (see Park and Iceland 2011: 816). It may not necessarily be the "newness" of a destination that matters for immigrant outcomes, but rather the institutional arrangements that are found within the destination (Waters and Jiménez 2005). As research on immigrants in new destinations proceeds, it will be increasingly important to recognize sources of heterogeneity within new destinations, rather than solely focus on comparisons between new and established destinations.

Approach

I argue that the literature on ethno-racial differences across destinations would benefit from the use of multilevel statistical models. These models can be used for data that exhibits a hierarchical structure, where one unit of analysis (individuals, for example) is nested in another unit of analysis (states, for example). Multilevel modeling can allow researchers to examine the factors that produce variation in immigrant outcomes across destinations, without defining destinations as new or established at the beginning of the analysis. I argue that the use of multilevel modeling would benefit the study of immigrants in new and other types of destinations in two ways. First, multilevel models allow researchers to refrain from defining destinations discretely as "new" or "established." This ensures that results are not sensitive to the criteria used to establish destination categories. Second, multilevel models allow researchers to examine how level 1 and level 2 factors influence variation in immigrant outcomes across destinations. These models can help researchers to determine whether variations in outcomes across destinations are due to compositional factors (individual and household characteristics) or contextual factors, such as a place's immigration history. In sum, multilevel models can help researchers to gauge the extent to which a destination's immigration history matters for a given outcome, compared to compositional factors and other contextual attributes.

In this analysis, I demonstrate the utility of a multilevel approach by analyzing patterns of school non-enrollment among Mexican origin 15-17 year-olds across U.S. states. I run a series of multilevel models where Mexican origin adolescents (level 1 unit of analysis) are nested in 50 states and the District of Columbia (level 2 unit of analysis). In these models, the intercept is allowed to vary by state. This produces a variance term for the intercept, which represents the overall between-state variance in the log odds of Mexican origin non-enrollment. The models also estimate random effects parameters for each state, which represent the state's deviation from the overall mean of the states' mean log odds of non-enrollment. These models thus quantify levels of variation in Mexican origin non-enrollment across states and identify states where Mexican origin adolescents have higher or lower than average probabilities of non-enrollment. In addition, covariates that produce changes in the variance of the intercept and the state random effects parameters provide information about the factors that drive variation in Mexican origin non-enrollment across states. As I will demonstrate, multilevel models shed light on the relative importance of individual background factors (immigrant generation, parental education, family status) and state-level factors (immigration history, peer composition, educational context) in shaping between-state differences in patterns of Mexican origin non-enrollment.

Data

For the analysis presented here, I use the individual and household records of 15-17 year-olds in the 2005-2009 American Community Survey (ACS), from the Integrated Public Use Microdata Series (Ruggles et al. 2010). I also create a file of state-level variables, using three datasets from IPUMS: the 1990 decennial census 5% state microdata sample (weighted), the 2010 ACS (1% probability sample, weighted), and the 2005-2009 ACS (an aggregate of five 1% probability samples from 2005-2009, weighted). To construct the sample for analysis, I extract the data records of all 15-17 year-olds in the 2005-2009 ACS. For 15-17 year-olds who live with one or two parents in the household, I merge the parental data record/s with the individual 15-17 year-old data record. For 15-17 year-olds who do not live with a parent in the household, I use the householder record as a proxy for the parental record.

A group of 15-17 year-olds does not live with parents and does not have an available householder record. This group includes individuals in group quarters (such as institutional inmates) and individuals who are the householder (i.e. the individual who filled out the survey). During the household record matching process, individuals who live in institutional group quarters are dropped from the analysis. Individuals who consider themselves the householder are included and the analysis, and are flagged using dummy variables in the analysis.

The final sample of non-institutionalized 15-17 year-olds in the 2005-2009 ACS includes 637,103 cases. Approximately 65.3 percent of 15-17 year-olds in the final sample are matched with both a mother and father record (both mother and father are located in the household), 22.2 percent are matched with a mother record, 6.1 percent are matched with a father record, 6.1 percent are matched with a householder record (no mother or father is present in the household), and .3 percent are not matched with a parental or householder record (no mother or father is present in the household and the 15-17 year-old is the householder).

For the multi-level analysis, I examine variation in school non-enrollment across states only for the Mexican origin 15-17 year-old population. A subject is identified as Mexican origin if he/she meets one or more the following criteria: 1) The subject was born in Mexico; 2) At least one of the subject's parents was born in Mexico; 3) The subject is identified as "Hispanic- Mexican" on the Hispanic origin question. Among the final 15-17 year-old sample in the 2005-2009 ACS, I identify approximately 71,269 subjects as adolescents of Mexican origin (11.2 percent of all 15-17 year-old cases). For some portions of the analysis, I create a subset of Non-Hispanic White (NH White) and Non-Hispanic Black (NH Black) 15-17 year-olds. There are approximately 357,701 NH White 15-17 year-old subjects in the 2005-2009 ACS dataset (70.6 percent of all 15-17 year-olds), and 66,438 NH Black 15-17 year-old subjects (13.11 percent of all 15-17 year-olds).

Variables

Individual-Level Variables (Level 1 Variables)

In the descriptive and multilevel analysis, I examine several individual-level variables that have been shown to predict levels of school non-enrollment and other educational outcomes. Immigrant generational status is a central variable in this study. As Rumbaut (2004) describes, immigrant generational categories indicate the degree of removal between those who engage in the act of migration and their descendants. Generational groups also encapsulate the degree of exposure that individuals have had to the receiving society and its institutions. In this analysis, I use an approximation of Rumbaut's (2004) typology to classify the Mexican origin population into four categories by nativity and age at arrival: The 1.25 generation, 1.5 generation, 1.75 generation, and the native-born, or second and higher generations. Hirschman (2001) finds a difference in the likelihood of school non-enrollment among foreign-born immigrant adolescents by age of arrival, which further justifies the use of Rumbaut's typology.

The 1.25 generation includes those who migrated after the age of 12-- the most recent arrivals. As several researchers note (Hirschman 2001; Oropesa and Landale 2009), some recent arrivals that are not enrolled in school may be labor migrants who never enroll in school in the United States. The 1.5 generation includes individuals who arrived between the ages of 6 and 12, and likely had some schooling in Mexico. These individuals will not face the same number of obstacles to integration as new arrivals, but may still experience problems due to the discontinuities associated with attending school in two different countries. The 1.75 generation are adolescents who arrived in the United States by the age of five. The 1.75 generation should be more integrated into the United States school system than the 1.5 and 1.25 generations, given that they have spent the majority of their school-aged lives in the United States. For this reason, the 1.75 generation is often considered comparable to the immigrant second generation (see, for example, Perlmann 2005, and Kasinitz et al. 2008).

The elimination of the parental birthplace question from the decennial census in 1980 makes it difficult for researchers to differentiate the immigrant second generation from the third and higher generations in census data (Hirschman 1994). This problem is not resolved in the ACS, which does include a parental birthplace question. The parental record matching technique described above helps me to identify parental birthplace in my analysis, but only for the subset of adolescents that are living with at least one parent. Thus, I cannot accurately identify the immigrant generational status of native-born Mexican origin individuals who do not live with either parent, or who live in single-parent households where the parent living in the household is native-born and the parent living outside the household is foreign-born. For this reason, I classify all second and higher generation immigrants together as native-born. I also identify non-citizens, who are foreign-born individuals that lack citizenship status, were not born abroad to American parents, and have not been naturalized. In multilevel logistic regressions, I do not control for citizenship status, because it is highly correlated with immigrant generational status. Approximately 93.5 percent of 1.25 generation Mexican origin adolescents are non-citizens, and 88.4 and 78.4 percent, respectively, of 1.5 and 1.75 generation Mexican origin adolescents are non-citizens.

Family structure is a powerful predictor of educational non-enrollment. Previous studies show that living in a single-parent family exerts a significant, negative impact on educational enrollment and high school completion (McLanahan 1985; Sandefur, McLanahan, and Wojtkiewicz 1992; Landale, Oropesa, and Llanes 1998; Hirschman 2001). For the Hispanic population, living in a single parent or stepparent family increases the odds of high school dropout or failure to complete a high school degree relative to individuals in two-parent family structures (Wojtkiewicz and Donato 1995; Landale, Oropesa, and Llanes 1998; Perreira, Harris, and Lee 2006).[4] For this analysis, I classify families as intact (two parents in the household), mother only, father only, or no parents present. I do not explore stepparent effects.

Status attainment models developed in the 1960s and 1970s showed that socio-economic origins, including parental educational attainment, had direct and indirect effects on children's adult educational attainment and occupational status (Blau and Duncan 1967; Duncan, Featherman, and Duncan 1972; Sewell and Hauser 1972). Kao and Thompson (2003) note that the socio-economic status of a student's family of origin continues to be highly predictive of white-nonwhite differences in educational outcomes such as school dropout. In specific studies of the Mexican origin population, parental educational attainment also exerts a major influence the educational outcomes of Mexican origin children (Landale, Oropesa, and Llanes 1998; Wojtkiewicz and Donato 1995; Zsembik and Llanes 1996).

[4] Perreira, Harris, and Lee (2006) observe no significant difference in the likelihood of high school completion between individuals in single mother households and those in two-parent households, but a significant, negative difference in the odds of high school completion between individuals in single father households and those in two-parent households.

In this analysis, I use parental educational attainment and poverty status as proxies for social origins. I collapse parental educational attainment into five levels: less than high school graduate (less than h.s.), high school degree or GED, some college, A.A. degree, and B.A. degree or higher. I also include a dummy variable to identify students who lack parental educational information because they do no have a parental or householder record. For individuals in intact households, I use the educational attainment level of the parent with the highest level of education.[5] For single-parent households, I use the level of educational attainment of the parent who is living in the household (mother or father). Finally, for individuals who do not live with parents, I use the level of educational attainment of the householder.

I use the poverty variable from the ACS dataset as a broad measure of household resources. The ACS poverty variable incorporates information on total family income, family size, number of children, and householder age to determine whether a family's poverty level is higher or lower than 100 percent of the poverty thresholds established by the Social Security Administration. I will demonstrate that, in multilevel logistic regression models, poverty has a negligible effect on non-enrollment, net of parental education. Thus, my conclusions are robust to the exclusion of the poverty variable from these models. I use the ACS poverty variable to classify families as living at three

[5] In a previous analysis (presented at the 2011 PAA Meeting, available upon request), I used the Bayesian Information Criterion (BIC) value for three logistic regression models regressing Mexican origin non-enrollment on parental education to determine which level of parental education to use for intact households (mother's versus father's). The BIC offers a means to assess model fit by incorporating information on the deviance (the likelihood ratio test statistic), the number of parameters in the model, and the sample size (see Raftery 1995: 133-136). Hauser (1995) has also advocated the use of the BIC as an important model selection tool in sociological research. I found that using the highest parental education level (for children in intact households) yielded the lowest BIC, and thus provided the best model fit for assessing the likelihood of school non-enrollment.

economic levels: below the poverty threshold (value on the poverty variable is less than 100 percent), one to two times the poverty threshold (poverty value is 100 to 200 percent of the threshold), or over two times the poverty threshold (poverty value is over 200 percent of the poverty threshold).

Student mobility is a major predictor of school dropout (Rumberger 2004). Student mobility contributes to school non-enrollment by destabilizing continuity in a student's schooling experience. The ACS provides information on whether the individual is residing in a place of residence that differs from their place of residence one year prior to the survey year (i.e. 1-year migration status). Using this information, I create a variable called "mobility" that captures three types of 1-year migration statuses: Intra-state migration, inter-state migration, and international migration. This measure is imperfect, because it does not differentiate types of within-state migration (intra- versus inter-metropolitan migration, inter-district migration, etc.) Still, this variable identifies individuals who have likely recently arrived in a new educational context.

Finally, I control for metropolitan status as if it were an individual-level predictor in the multilevel models (rather than a state-level predictor). I control for central city status, non-metropolitan status, and "other" metropolitan status (metropolitan status not identifiable, metropolitan- outside central city, and metropolitan- central city status unknown). The barriers that the central city imposes on the educational success of the children of immigrants are well documented, and include bifurcated labor markets, exposure to oppositional subcultures or gangs, and segregation in low quality schools (Kasinitz et al. 2008; Portes and Rumbaut 2001; Portes and Zhou 1993; Zhou 1997a; Zhou 1997b; Smith 2006). As discussed, Latinos are increasingly living outside of the central city, in both suburban and non-metropolitan areas (Hardwick 2008; Kandel and Cromartie 2004). Data on the effects of non-metropolitan status on school non-enrollment are mixed (see Reeves and Bylund's 2005; Rumberger and Palardy 2005). Case studies of rural new immigrant destinations, however, suggest that rural areas may lack the necessary resources to meet the specific linguistic and educational needs of newly arrived immigrant children (Gouveia, Carranza, and Cogua 2005). Thus, it is important to control for non-metropolitan status in the models.

State-level Variables (Level 2 Variables)

After controlling for individual-level variables that could potentially influence school non-enrollment differences across states (compositional factors), I introduce several state-level variables into the multilevel models. I divide state-level variables into three groups: Immigration history, peer composition, and educational context. Ideally, I would use a range of variables to measure these constructs. In practice, however, many state-level variables are highly correlated. For instance, the baseline foreign-born population in the state in 1990 and the state's foreign-born growth rate (immigration history variables) are highly correlated with the percent of NH White peers (15-17 year-olds) living in the state. Thus, the composition of the population within the state is highly influenced by patterns of migration into the state. Similarly, the percent of NH Black peers (15-17 year-olds) living in the state (a potential peer composition variable) is highly correlated with the percent of adults in the state who do not have a high school degree (a potential educational context variable). This multicollinearity leads to highly inflated standard errors in the multilevel models. For this reason, I only control for five state-level variables that are intended to represent immigration history, peer composition, and educational context.

Immigration history variables include the two standard covariates that are utilized to create destination typologies— foreign-born presence in a baseline year and foreign-born growth rates between the baseline year and a subsequent time period. I calculate the total and percent foreign-born individuals for each state (all ages) in 1990, using data from the 5% decennial census microdata file. I then calculate the total and percent foreign-born population (all ages) in 2010, using the 2010 ACS. Finally, I calculate foreign-born growth rates (percent) from 1990 to 2010. The inclusion of variables representing a state's immigration history should reduce between-state variance in the log odds of non-enrollment among Mexican origin adolescents. To the extent that living in a new versus an established destination affects the probability of Mexican origin non-enrollment, I should observe two types of results. First, the addition of immigration history variables should reduce between-state variance in the likelihood of non-enrollment, net of compositional factors. Second, these coefficients should be significant predictors of Mexican origin non-enrollment, net of compositional factors.

As discussed, recent work by Fischer (2010) finds that the likelihood of school non-enrollment is greater for 15-17 year-olds living in new destinations than for those living in established maintaining destinations. To the extent that Fischer's findings are generalizable to this study, the signs of the coefficients should reflect an established destination advantage. The log odds coefficient for the percent foreign-born in 1990 should have a negative sign, indicating that increases in the percentage of foreign-born individuals living in the state in 1990 (i.e. established destinations) are associated with lower log odds of non-enrollment. Conversely, the sign for the log odds coefficient for foreign-born growth rates between 1990 and 2010 should be positive, which would imply that increases in the foreign-born growth rate increase the likelihood of Mexican origin school non-enrollment.

Previous research on new immigrant destinations hypothesizes that variations in the institutional arrangements within destinations could differentially shape immigrant outcomes related to assimilation (Waters and Jiménez 2005). As discussed, researchers are only beginning to understand how contextual factors shape immigrant outcomes across destinations, with varying results. This poses difficulties for the identification of other state-level variables that might influence variation in Mexican origin school non-enrollment across states beyond immigration history. Nonetheless, I focus on two other sets of state characteristics that could hypothetically influence school non-enrollment patterns across states—peer composition and educational context.

The first variable represents minority peer composition. I calculate the percentage of NH Black 15-17 year-olds living in each state, using the 2005-2009 ACS. I hypothesize that Mexican origin adolescents living in states with higher percentages of NH Black peers may have a greater likelihood of school non-enrollment, because they may be competing with these students for resources that support minority education. Additionally, the high correlation between the percent of NH Black adolescents in the state and the percentage of adults (ages 25-64) in the state that lack a high school degree (.63, author's calculations; correlation matrix available upon request) means that the percent of NH Black peers in the state may also be a proxy for the overall quality of the educational context for minorities within the state.

The next set of variables tries to capture the context of high school dropout within each state. I calculate the percentage of NH White and NH Black 15-17 year-olds that are not enrolled in school for each state, using the 2005-2009 ACS. The basic hypothesis is that the overall quality of the state education system is likely to affect everyone living in the state. Poor quality education systems should produce higher rates of non-enrollment among all subgroups. Thus, increases in the percent of NH White and NH Black peers who drop out of school within the state should increase the likelihood of school non-enrollment among Mexican origin 15-17 year-olds.

Analytical Strategy

I begin the analysis by quantifying state-level variations in the distribution of Mexican origin adolescents across and within states (Table 1). I then analyze the dependent variable of interest—school non-enrollment. I first examine levels of school non-enrollment among Mexican origin, NH White, and NH Black adolescents across states (Table 2). In the ACS, school enrollment status is reported for each person in the household by the householder—the individual who fills out the survey. Individuals who are not enrolled in school at the time of the ACS survey could be considered dropouts. However, it is possible that these individuals may return to school at a future point in time. Thus, non-enrollment at ages 15-17 should not be considered a permanent dropout status. I also calculate the overall means of the individual-level variables for the Mexican origin, NH White, and NH Black populations, as well as several state-level characteristics. These results are displayed in the Appendix, Tables 1 and 2. I use person-level weights in the calculations of all descriptive statistics.

In the multivariate portion of the analysis, I run a series of stepwise multilevel logistic regression models, with school non-enrollment (y=1) as the binary outcome. I run all models in Stata 12.0, then repeat the analysis using R software to create the state random effects figures displayed in the Findings section. I do not use weights in the multilevel regression analysis. The multilevel logistic regression models in this analysis allow the intercept of the log odds of Mexican origin non-enrollment to vary by state. The baseline model is as follows:

$$\log it(P[Y_{non-enroll} = 1]) = \alpha_{j[i]} + \beta_{age} * age_i + \beta_{sex} * sex_i, i = 1...n$$

$$\alpha_{j[i]} \sim N(\mu_\alpha, \sigma^2{}_{state}), j = 1,...51$$

The baseline model includes controls for age and sex. Of particular interest in this and subsequent models is $\sigma^2{}_{state}$, the between-state variance in the log odds of Mexican origin non-enrollment. For each model, I display the random effects parameters for each state, which represent state differences from the overall mean of the state means of the log odds of Mexican origin non-enrollment. To the extent that individual and state-level attributes explain between-state differences in the likelihood of Mexican origin non-enrollment, this parameter should decrease in magnitude as covariates are added to the models. I next add a series of individual-level (level 1) covariates to the baseline model:

$$\log it(P[Y_{non-enroll} = 1]) = \alpha_{j[i]} + \beta_{age} * age_i + \beta_{sex} * sex_i + \mathrm{B}_{level1} * level1_i, i = 1...n$$

$$\alpha_{j[i]} \sim N(\mu_\alpha, \sigma^2{}_{state}), j = 1,...51$$

Next, I add the state-level covariates to the model controlling for all individual-level covariates:

$$\log it(P[Y_{non-enroll}=1]) = \alpha_{j[i]} + \beta_{age} * age_i + \beta_{sex} * sex_i + \mathrm{B}_{level1} * level1_i + \mathrm{B}_{level2} * level2_{ij}, i = 1...n$$

$$\alpha_{j[i]} \sim N(\mu_\alpha, \sigma^2{}_{state}), j = 1,...51$$

State-level covariates that reduce the between-state variance in the likelihood of non-enrollment ($\sigma^2{}_{state}$), net of individual-level factors, provide information about the attributes of destinations that shape patterns of non-enrollment across states.

Findings

State-level distributions of Mexican origin adolescents

Table 1 displays the distribution of Mexican origin 15-17 year-olds across states, as well as the percentage of 15-17 year-olds of Mexican origin adolescents within states. Despite the emergence of new destinations, California and Texas remain major areas of settlement for the Mexican origin population. The majority of all Mexican origin adolescents (64.4 percent) live in California and Texas. A noticeable share (13.1 percent) of the Mexican origin population also lives in the established Mexican origin gateways of Arizona, Illinois, and Colorado. A number of states individually receive only 1-2 percent of all Mexican origin 15-17 year-olds, but these states cumulatively receive 12.5 percent of all Mexican origin adolescents. These states are spread across regions of the U.S., and include Washington, New Mexico, Nevada, Florida, Georgia, Oregon, New York, North Carolina, and Michigan. Finally, the remaining 10 percent of all Mexican origin 15-17 year-olds are dispersed across 37 states and the District of Columbia. These distributions show that established patterns of Mexican origin settlement prevail. Most 15-17 year-olds of Mexican origin live in the Southwestern states and Illinois. However, consonant with the new destinations literature, a noticeable share (around 22.5 percent) of Mexican origin adolescents live outside of these established gateway areas.

The between-state and within-state distributions of Mexican origin 15-17 year-olds are highly correlated (.75). States that attract a greater share of the total Mexican origin 15-17 year-old population also tend to have higher than average proportions of Mexican origin adolescents living within the state. Over 30 percent of all 15-17 year-olds in California, Texas, and Arizona, are adolescents of Mexican origin. A large proportion of 15-17 year-olds living in New Mexico and Nevada (approximately 26 percent and 31 percent, respectively) are of Mexican origin.

Importantly, in some states that receive smaller shares of all Mexican origin adolescents (less than 5% each), Mexican origin adolescents make up a noticeable proportion of all 15-17 year-olds within the state. This speaks to the state-level impact of the geographic dispersion of immigrants. For instance, even though only .7 percent of all Mexican origin 15-17 year-olds live in Kansas, nearly 1 in 10 adolescents in the state of Kansas is of Mexican origin. Additionally, while many states have relatively small proportions of Mexican origin adolescents, it is important to remember that these individuals are unlikely to be distributed randomly throughout the state. In other words, state-level distributions may mask uneven concentrations of Mexican origin adolescents at lower levels of geography within the state.

Table 1. Between and Within-State Distributions of Mexican Origin 15-17 Year-olds (Ordered), 2005-2009 ACS.

State	Percent Mexican Origin Across States	State	Percent Mexican Origin Within States
California	39.90	California	38.84
Texas	24.47	Texas	36.74
Arizona	5.95	Arizona	35.11
Illinois	4.92	New Mexico	31.25
Colorado	2.24	Nevada	25.74
Washington	1.80	Colorado	17.97
New Mexico	1.72	Illinois	14.23
Nevada	1.71	Idaho	11.98
Florida	1.68	Oregon	11.86
Georgia	1.30	Washington	10.56
Oregon	1.13	Utah	9.38
New York	1.10	Kansas	9.22
North Carolina	1.06	Oklahoma	8
Michigan	1.02	Nebraska	7.7
Oklahoma	0.77	Wyoming	6.22
Indiana	0.75	Arkansas	5.19
Utah	0.74	Georgia	4.98
Kansas	0.69	North Carolina	4.6
Wisconsin	0.66	Wisconsin	4.39
Idaho	0.51	Indiana	4.36
Minnesota	0.48	Delaware	4.01
Ohio	0.44	Iowa	3.95
New Jersey	0.44	Florida	3.75
Missouri	0.41	Michigan	3.62
Tennessee	0.40	Alaska	3.49
Arkansas	0.39	Minnesota	3.4
Nebraska	0.37	Hawaii	2.94
Virginia	0.35	South Dakota	2.84
Iowa	0.31	Missouri	2.55
Pennsylvania	0.27	Tennessee	2.52
South Carolina	0.26	Montana	2.44
Alabama	0.24	South Carolina	2.2
Kentucky	0.19	New York	2.17
Maryland	0.19	Alabama	1.94
Louisiana	0.16	New Jersey	1.92
Connecticut	0.14	North Dakota	1.89
Massachusetts	0.13	Virginia	1.78
Mississippi	0.10	Kentucky	1.75
Hawaii	0.09	District of Columbia	1.55
Delaware	0.09	Connecticut	1.5
Wyoming	0.08	Ohio	1.42
Alaska	0.07	Louisiana	1.31
Montana	0.06	Mississippi	1.24
South Dakota	0.06	Maryland	1.22
West Virginia	0.05	West Virginia	1.06
North Dakota	0.03	Pennsylvania	0.81
New Hampshire	0.03	New Hampshire	0.78
District of Columbia	0.02	Massachusetts	0.77
Rhode Island	0.02	Rhode Island	0.62
Maine	0.01	Vermont	0.42
Vermont	0.01	Maine	0.41
Total	100.00		

Non-enrollment patterns across states

Consistent with previous analyses, the 2005-2009 ACS data show that Mexican origin adolescents have higher than average non-enrollment rates compared to their peers. Approximately 6.7 percent of all Mexican origin 15-17 year-olds are not enrolled in school, compared to 3.5 percent of all NH White 15-17 year-olds and 4.3 percent of all NH Black 15-17 year-olds. Table 2 displays school non-enrollment rates for each of these groups by state. There is considerable variation in rates of school non-enrollment among Mexican origin adolescents across states, ranging from negligible levels of non-enrollment in states with very small Mexican origin populations, such as Maine and New Hampshire, to 28.1 percent non-enrollment in Alabama. Non-enrollment rates among NH Whites and NH Blacks also vary by state, but to a lesser degree. In fact, the standard deviation for the overall non-enrollment rate for Mexican origin adolescents is higher than the standard deviations of non-enrollment for the NH White and NH Black populations, indicating that this population has a more variable distribution of non-enrollment.

The non-enrollment rate among Mexican origin adolescents in California is 4.3 percent, which is lower than the average for the total Mexican origin 15-17 year-old population. This is surprising, given the emphasis in the previous literature on a trend towards downward assimilation among some Mexican origin adolescents in major immigrant gateways in California, such as San Diego (Portes and Rumbaut 2001). In Texas, the Mexican origin non-enrollment rate is 6.2 percent, just slightly lower than the average level of Mexican origin non-enrollment.

Table 2. Percent School Non-Enrollment Among Mexican Origin, Non-Hispanic White, and Non-Hispanic Black 15-17 Year-olds, by State, 2005-2009 ACS.

State	Percent	Pop. Total	n	Percent	Pop. Total	n	Percent	Pop. Total	n
Alabama	28.1	3,779	153	4.6	122,475	6,524	4.2	61,298	2,751
Alaska	7.3	1,153	59	4.7	19,086	835	11.8	1,046	43
Arizona	7.4	93,796	4,154	4.8	127,250	6,406	3.9	11,184	447
Arkansas	16.8	6,175	312	5.6	83,543	4,312	4.6	23,342	997
California	4.3	629,149	28,723	2.4	555,252	28,778	2.8	111,477	4,361
Colorado	11.2	35,320	1,569	3.8	128,992	6,929	4.1	9,019	342
Connecticut	5.0	2,240	95	2.2	102,087	5,416	5.2	16,874	672
Delaware	16.8	1,438	51	4.3	22,258	1,084	3.5	9,261	333
District of Columbia	0.0	291	10	0.0	2,069	107	6.3	14,443	655
Florida	16.3	26,457	1,269	4.7	373,321	19,087	4.8	143,008	6,138
Georgia	16.1	20,487	827	3.9	216,332	11,352	4.4	145,627	6,428
Hawaii	1.4	1,447	78	5.8	7,783	367	4.6	1,032	22
Idaho	11.4	8,028	375	3.7	54,915	2,957	4.8	294	15
Illinois	6.0	77,592	3,128	2.4	322,275	18,460	4.3	100,703	3,669
Indiana	7.7	11,792	529	4.1	218,166	11,762	5.3	27,626	1,089
Iowa	6.1	4,889	219	3.5	109,628	5,825	2.3	3,759	117
Kansas	8.4	10,814	466	2.7	90,946	5,032	5.2	7,844	316
Kentucky	16.2	3,014	111	4.4	147,776	7,698	4.5	15,505	694
Louisiana	12.2	2,536	131	4.7	106,223	5,540	5.3	74,687	3,025
Maine	0.0	222	17	4.2	50,217	2,374	10.3	835	26
Maryland	8.4	2,945	180	4.0	130,186	7,222	4.1	78,978	3,175
Massachusetts	10.3	1,972	96	2.6	191,514	10,338	4.9	18,699	743
Michigan	5.0	16,162	770	3.5	321,384	17,717	6.0	81,348	2,715
Minnesota	12.2	7,496	276	2.1	179,443	10,525	5.6	10,894	338
Mississippi	25.1	1,616	69	5.1	66,425	3,419	4.5	58,592	2,830
Missouri	9.9	6,428	325	4.5	196,096	10,348	5.8	36,015	1,424
Montana	10.4	1,002	45	6.3	33,924	1,702	6.7	238	7
Nebraska	4.7	5,786	241	2.0	60,938	3,493	3.2	4,147	122
Nevada	10.0	26,911	1,208	6.4	51,610	2,627	4.5	9,821	409
New Hampshire	0.0	441	19	2.7	52,202	2,644	0.0	609	21
New Jersey	17.4	6,955	305	2.3	213,327	11,813	4.3	56,159	2,393
New Mexico	7.1	27,059	1,214	4.9	26,706	1,309	2.8	2,065	63
New York	14.6	17,410	634	2.7	444,419	25,634	3.8	141,273	5,334
North Carolina	15.1	16,785	748	4.5	224,428	11,724	4.0	95,502	4,262
North Dakota	11.0	498	15	4.4	22,637	1,296	6.6	228	8
Ohio	4.3	6,997	354	3.3	388,469	20,539	4.0	70,905	2,853
Oklahoma	9.5	12,100	581	3.9	97,109	4,983	2.7	13,519	472
Oregon	9.1	17,782	802	4.7	114,069	5,806	0.7	2,958	108
Pennsylvania	15.0	4,196	163	3.9	396,587	21,771	3.8	68,501	2,104
Rhode Island	9.4	265	15	2.9	31,128	1,604	9.3	2,644	104
South Carolina	19.3	4,037	186	3.9	106,348	5,640	3.6	65,414	2,739
South Dakota	1.5	971	31	3.3	27,784	1,504	0.0	224	7
Tennessee	19.0	6,333	307	3.4	181,496	9,429	3.7	53,186	2,140
Texas	6.2	385,872	17,791	3.1	431,102	23,696	3.4	135,042	5,611
Utah	6.5	11,597	489	2.6	99,614	5,346	0.7	1,234	50
Vermont	0.0	111	6	3.5	24,734	1,244	7.7	286	8
Virginia	15.6	5,562	286	2.7	194,753	10,526	3.7	72,640	3,205
Washington	6.3	28,380	1,333	3.6	191,604	10,108	4.6	9,902	389
West Virginia	16.2	727	30	5.1	63,688	3,221	9.4	2,298	99
Wisconsin	7.3	10,477	393	2.5	190,855	11,155	7.1	19,209	533
Wyoming	8.3	1,329	81	4.9	18,174	947	0.0	247	4
Total		1,576,821	71,269		7,633,347	410,175		1,891,641	76,410
Pop. Mean	6.7			3.5			4.3		
Pop. Std. Dev.	25.0			18.3			20.2		

The disproportionate number of Mexican origin adolescents living in California and Texas shifts the average level of Mexican origin non-enrollment downward. When Mexican origin adolescents in California and Texas are dropped from the sample, the overall rate of Mexican origin non-enrollment increases to 9.7 percent (author's calculation). Importantly, the descriptive analysis of Mexican origin non-enrollment rates by state helps to justify the use of multilevel modeling. There is notable between-state variation in rates of non-enrollment among Mexican origin adolescents, and multilevel modeling will reveal how individual and state-level characteristics influence this heterogeneity.

Multilevel models: Between-state variance in the log odds of Mexican origin non-enrollment

As discussed, I restrict the multilevel analysis to the Mexican origin 15-17 year-old sample in the 2005-2009 ACS (n=71,269). Table 3 displays the results for a series of stepwise multilevel logistic regression models, with school non-enrollment as the dependent variable. In this section, I mainly focus on a discussion of the determinants of between-state variation in the log odds of Mexican origin non-enrollment. However, I make note of the significance of the log odds coefficients when relevant. Of particular interest are the variance of the intercept (state) in the "random effects" row at the bottom of Table 3, and the ordered state random effects parameters, displayed in Table 4. The state random effects parameters indicate how the states' mean log odds of non-enrollment deviate from the overall mean of the state means. States with positive random effects values represent states that have higher mean log odds of non-enrollment relative to the overall mean of the state means. Conversely, states with negative random effects values have lower mean log odds of non-enrollment relative to the overall mean of the state means. Substantively, positive random effects values should point to states with negative schooling contexts, whereas negative random effects values should represent states with positive schooling contexts. I am hesitant, however, to make firm statements about the quality of schooling contexts within states based on the random effects values, as some portion of the between-state variance is due to compositional factors (as I will demonstrate) and another portion of the variance is likely due to unmeasured heterogeneity. (Non-ordered random effects parameters for each state and each model are listed in the Appendix, Table A3.)

In the first model (Model 1), which only controls for age and sex, the variance of the intercept is .20. In this model, the five states with the largest positive random effects include Alabama, Kentucky, Mississippi, New Jersey, and South Carolina, and the five states with the largest negative random effects (lowest mean likelihoods of non-enrollment) include California, Nebraska, Wisconsin, Ohio, and Texas (see Table 4 and Figure 1). The baseline model indicates that, before controlling for compositional factors, non-enrollment is particularly high among Mexican origin adolescents in some of the Southern states and New Jersey. In contrast, non-enrollment appears to be lower than average in the established gateways of California and Texas, and the Midwestern states of Nebraska, Wisconsin, and Ohio.

When immigrant generation variables are introduced in the model (Table 3, Model 2), the variance in Model 1 is reduced by over 50% (to .09). This indicates that a substantial portion of the baseline between-state variance in log odds of non-enrollment can be attributed to the unequal distribution of Mexican origin adolescents with different generational statuses (nativity statuses and years of residence) across states.

Table 3. Fixed and Random Effects Estimates from Multilevel Logistic Regression Models of School Non-Enrollment to Enrollment, Mexican Origin 15-17 year-olds, 2005-2009 ACS.

	Model 1		Model 2		Model 3		Model 4		Model 5	
Fixed Effects	log odds	p	log odds	p	log odds	p	log odds	p	log odds	p
Individual Level										
Demographics										
Age 16	0.61	0.000	0.51	0.000	0.47	0.000	0.48	0.000	0.48	0.000
Age 17	1.47	0.000	1.30	0.000	1.24	0.000	1.24	0.000	1.25	0.000
(Ref. is Age 15)										
Male	0.26	0.000	0.17	0.000	0.17	0.000	0.18	0.000	0.18	0.000
(Ref. is Female)										
Immigrant Generation										
1.25 Generation			2.57	0.000	2.02	0.000	1.91	0.000	1.91	0.000
1.5 Generation			0.93	0.000	0.73	0.000	0.72	0.000	0.71	0.000
1.75 Generation			0.61	0.000	0.49	0.000	0.49	0.000	0.49	0.000
(Ref. is Native-Born)										
Family Status in Household										
No parents in HH					1.62	0.000	1.52	0.000	1.52	0.000
Mother, no Father					0.52	0.000	0.47	0.000	0.47	0.000
Father, no Mother					0.74	0.000	0.69	0.000	0.69	0.000
(Ref. is Intact)										
Parental Education										
No parent or HH record					1.84	0.000	1.78	0.000	1.78	0.000
Less than HS					0.94	0.000	0.96	0.000	0.96	0.000
HS Degree or GED					0.67	0.000	0.67	0.000	0.67	0.000
Some College					0.31	0.001	0.31	0.001	0.31	0.001
AA					0.24	0.052	0.24	0.057	0.24	0.057
(Ref. is BA and BA+)										
Poverty Status										
Below Poverty					0.08	0.078	0.04	0.403	0.04	0.409
1-2x Pov. Threshold					0.07	0.133	0.05	0.232	0.05	0.235
(Ref. is 2X + Pov. Threshold)										
Metropolitan Status										
Central City							0.16	0.001	0.16	0.001
Non-metropolitan							-0.02	0.678	-0.03	0.598
(Ref. is other metro or metro not identified)										
Mobility										
Recent mobility (1 yr.)							0.57	0.000	0.57	0.000
(Ref. is no mobility, 1yr.)										
State Level										
Immigration History										
1990 Foreign Born (%)									-0.01	0.236
1990-2010 FB Growth (%)										
Peer Composition										
NH Black 15-17 year-olds (%)										
Educational Context										
NH White peer non-enrollment (%)										
NH Black peer non-enrollment										
Intercept	-3.42	0.000	-3.81	0.000	-4.87	0.000	-4.95	0.000	-4.98	0.000
Random Effects	Var.	Std. Err.	Var.	Std. Err.	Var.	Std. Err.	Var.	Std. Err.	Var.	Std. Err.
Intercept (State)	0.200	0.054	0.090	0.029	0.091	0.029	0.095	0.031	0.090	0.030
BIC	28813.1		26381.9		24697.7		24556.2		24566.02	
n	71269		71269		71269		71269		71269	

(Table 3 Cont'd.)

	Model 6		Model 7		Model 8		Model 9	
Fixed Effects	log odds	p	log odds	p	log odds	p	log odds	p
Individual Level								
Demographics								
Age 16	0.48	0.000	0.48	0.000	0.48	0.000	0.483	0.000
Age 17	1.24	0.000	1.24	0.000	1.25	0.000	1.245	0.000
(Ref. is Age 15)								
Male	0.18	0.000	0.18	0.000	0.18	0.000	0.178	0.000
(Ref. is Female)								
Immigrant Generation								
1.25 Generation	1.91	0.000	1.91	0.000	1.90	0.000	1.908	0.000
1.5 Generation	0.71	0.000	0.71	0.000	0.71	0.000	0.715	0.000
1.75 Generation	0.49	0.000	0.49	0.000	0.49	0.000	0.492	0.000
(Ref. is Native-Born)								
Family Status in Household								
No parents in HH	1.52	0.000	1.52	0.000	1.51	0.000	1.515	0.000
Mother, no Father	0.47	0.000	0.47	0.000	0.47	0.000	0.466	0.000
Father, no Mother	0.69	0.000	0.69	0.000	0.68	0.000	0.684	0.000
(Ref. is Intact)								
Parental Education								
No parent or HH record	1.77	0.000	1.77	0.000	1.77	0.000	1.767	0.000
Less than HS	0.95	0.000	0.95	0.000	0.95	0.000	0.953	0.000
HS Degree or GED	0.67	0.000	0.67	0.000	0.67	0.000	0.672	0.000
Some College	0.31	0.001	0.31	0.001	0.31	0.001	0.304	0.001
AA	0.24	0.058	0.24	0.058	0.24	0.057	0.234	0.061
(Ref. is BA and BA+)								
Poverty Status								
Below Poverty	0.04	0.411	0.05	0.413	0.04	0.410	0.040	0.411
1-2x Pov. Threshold	0.05	0.239	0.05	0.239	0.05	0.235	0.055	0.232
(Ref. is 2X + Pov. Threshold)								
Metropolitan Status								
Central City	0.16	0.000	0.16	0.000	0.16	0.000	0.168	0.077
Non-metropolitan	-0.03	0.641	-0.03	0.611	-0.03	0.624	-0.030	0.610
(Ref. is other metro or metro not identified)								
Mobility								
Recent mobility (1 yr.)	0.57	0.000	0.57	0.000	0.57	0.000	0.572	0.000
(Ref. is no mobility, 1yr.)								
State Level								
Immigration History								
1990 Foreign Born (%)			-0.01	0.640	-0.01	0.654	-0.002	0.854
1990-2010 FB Growth (%)	0.00	0.074	0.00	0.164	0.00	0.205	0.000	0.823
Peer Composition								
NH Black 15-17 year-olds (%)					0.00	0.367	0.005	0.254
Educational Context								
NH White peer non-enrollment (%)							0.164	0.001
NH Black peer non-enrollment							0.012	0.727
Intercept	4.98	0.000	4.99	0.000	4.98	0.000	5.00	0.000
Random Effects	Var.	Std. Err.	Var.	Std. Err.	Var.	Std. Err.	Var.	Std. Err.
Intercept (State)	0.084	0.028	0.084	0.028	0.080	0.027	0.056	0.021
BIC	24564.35		24575.31		24585.69		24597.67	
n	71269		71269		71269		71269	

Table 4. Random Effects Estimates by State (Ordered) for Multilevel Logistic Regression Models of Non-Enrollment to Enrollment, Mexican Origin 15-17 Year-olds, 2005-2009 ACS.

State	Model 1	State	Model 2	State	Model 3	State	Model 4	State	Model 5
Alabama	0.814	Florida	0.438	Florida	0.471	Florida	0.504	Florida	0.595
Kentucky	0.612	Alabama	0.406	Missouri	0.412	Missouri	0.398	New Jersey	0.413
Mississippi	0.610	Missouri	0.358	Alabama	0.391	Alabama	0.398	Alabama	0.355
New Jersey	0.606	Nevada	0.322	Colorado	0.325	New Jersey	0.344	Missouri	0.354
South Carolina	0.578	New Jersey	0.293	Nevada	0.313	Colorado	0.313	Nevada	0.336
Georgia	0.551	Colorado	0.275	Kentucky	0.311	Kentucky	0.305	Colorado	0.298
Florida	0.559	Virginia	0.256	New Jersey	0.303	Nevada	0.301	Kentucky	0.267
North Carolina	0.528	Mississippi	0.254	Virginia	0.255	Idaho	0.275	Virginia	0.258
Virginia	0.448	Georgia	0.254	Idaho	0.243	Virginia	0.264	Idaho	0.246
Delaware	0.419	Kentucky	0.244	North Dakota	0.193	Georgia	0.204	New York	0.195
New York	0.404	North Dakota	0.180	Georgia	0.179	North Dakota	0.193	North Dakota	0.180
Tennessee	0.327	Oregon	0.177	Oregon	0.148	Oregon	0.157	Georgia	0.171
Arkansas	0.298	Idaho	0.174	West Virginia	0.131	South Carolina	0.135	Oregon	0.140
Missouri	0.260	New York	0.166	South Carolina	0.124	Delaware	0.134	Delaware	0.112
North Dakota	0.257	South Carolina	0.162	Delaware	0.116	Mississippi	0.124	South Carolina	0.120
Nevada	0.163	Delaware	0.156	Kansas	0.116	West Virginia	0.114	West Virginia	0.111
Idaho	0.152	North Carolina	0.139	Mississippi	0.112	Kansas	0.109	Mississippi	0.098
West Virginia	0.149	West Virginia	0.113	New York	0.109	Louisiana	0.102	Massachusetts	0.094
Pennsylvania	0.142	Montana	0.084	Louisiana	0.096	Pennsylvania	0.078	Kansas	0.079
Colorado	0.110	Arkansas	0.079	Montana	0.081	Massachusetts	0.077	Louisiana	0.078
Oregon	0.057	Kansas	0.077	Massachusetts	0.079	Montana	0.071	Pennsylvania	0.061
Louisiana	0.027	Pennsylvania	0.066	North Carolina	0.052	New York	0.070	Montana	0.059
Montana	0.026	Tennessee	0.053	Pennsylvania	0.042	North Carolina	0.044	Rhode Island	0.035
Massachusetts	0.036	Massachusetts	0.046	Rhode Island	0.030	Rhode Island	0.034	North Carolina	0.000
Rhode Island	-0.004	Oklahoma	0.025	Vermont	-0.013	New Mexico	0.001	New Mexico	-0.001
Oklahoma	0.023	Rhode Island	0.012	Tennessee	0.015	Vermont	0.013	Vermont	0.013
Vermont	-0.073	Louisiana	0.021	Arkansas	-0.019	Arkansas	-0.018	Arizona	-0.025
Kansas	-0.083	Vermont	-0.024	Oklahoma	-0.023	Tennessee	-0.019	Wyoming	-0.049
Minnesota	-0.088	Wyoming	-0.046	New Mexico	-0.025	Wyoming	-0.035	Tennessee	-0.059
Indiana	-0.123	Arizona	-0.049	Wyoming	-0.037	Oklahoma	-0.041	Arkansas	-0.050
Wyoming	-0.137	New Mexico	-0.060	Arizona	-0.045	Arizona	-0.050	New Hampshire	-0.050
District of Columbia	-0.156	South Dakota	-0.067	New Hampshire	-0.063	New Hampshire	-0.062	Oklahoma	-0.076
South Dakota	-0.170	New Hampshire	-0.071	Alaska	-0.073	Indiana	-0.087	Alaska	-0.088
Iowa	-0.175	Maine	-0.107	Maine	-0.089	Alaska	-0.080	Hawaii	-0.092
Maryland	-0.177	Iowa	-0.107	Indiana	-0.099	Maine	-0.105	Maine	-0.133
Arizona	0.197	Alaska	0.113	Iowa	0.100	Iowa	0.106	Indiana	0.125
New Hampshire	-0.213	Minnesota	-0.113	Minnesota	-0.118	Hawaii	-0.125	Iowa	-0.131
Maine	-0.217	District of Columbia	-0.135	Hawaii	-0.125	Utah	-0.126	Utah	-0.144
Utah	-0.279	Utah	-0.141	Utah	-0.131	Minnesota	-0.139	South Dakota	-0.145
Alaska	-0.298	Indiana	-0.143	South Dakota	-0.140	South Dakota	-0.141	Minnesota	-0.159
New Mexico	-0.332	Hawaii	-0.167	Michigan	-0.157	Michigan	-0.156	District of Columbia	-0.170
Washington	-0.336	Michigan	-0.178	District of Columbia	-0.171	District of Columbia	-0.183	Michigan	-0.176
Connecticut	-0.353	Washington	-0.271	Maryland	-0.201	Maryland	-0.200	Maryland	-0.199
Illinois	-0.413	Illinois	-0.284	Illinois	-0.242	Illinois	-0.273	Illinois	-0.241
Michigan	-0.416	Maryland	-0.290	Ohio	-0.265	Washington	-0.279	Connecticut	-0.259
Hawaii	-0.441	Texas	-0.291	Connecticut	-0.275	Connecticut	-0.286	Washington	-0.252
Texas	-0.469	Ohio	-0.292	Washington	-0.282	Ohio	-0.286	Texas	-0.256
Wisconsin	-0.498	Connecticut	-0.303	Texas	-0.299	Texas	-0.309	Ohio	-0.307
Ohio	-0.517	Wisconsin	-0.343	Wisconsin	-0.365	Wisconsin	-0.389	Wisconsin	-0.410
Nebraska	-0.560	Nebraska	-0.402	Nebraska	-0.415	Nebraska	-0.401	California	-0.415
California	-0.805	California	-0.593	California	-0.615	California	-0.617	Nebraska	-0.416

(Table 4 Cont'd.)

State	Model 6	State	Model 7	State	Model 8	State	Model 9
Florida	0.545	Florida	0.578	Florida	0.542	New Jersey	0.431
New Jersey	0.399	New Jersey	0.420	New Jersey	0.401	Colorado	0.325
Missouri	0.396	Missouri	0.378	Missouri	0.369	Florida	0.324
Alabama	0.357	Alabama	0.345	Colorado	0.307	Virginia	0.281
Colorado	0.269	Colorado	0.268	Alabama	0.298	Idaho	0.262
Virginia	0.258	Virginia	0.256	Idaho	0.275	Missouri	0.238
Kentucky	0.249	Kentucky	0.241	Kentucky	0.247	Kansas	0.205
Idaho	0.247	Idaho	0.238	Virginia	0.225	New York	0.200
North Dakota	0.180	New York	0.216	Oregon	0.199	Alabama	0.199
New York	0.178	North Dakota	0.177	New York	0.189	Kentucky	0.184
Oregon	0.166	Oregon	0.160	Nevada	0.184	North Dakota	0.115
Louisiana	0.132	Nevada	0.155	North Dakota	0.171	Oregon	0.106
West Virginia	0.127	West Virginia	0.122	West Virginia	0.120	Massachusetts	0.102
Mississippi	0.126	Louisiana	0.119	Kansas	0.116	Delaware	0.061
Delaware	0.120	Delaware	0.117	Massachusetts	0.109	West Virginia	0.060
Nevada	0.116	Mississippi	0.115	Delaware	0.100	Pennsylvania	0.056
Pennsylvania	0.111	Massachusetts	0.107	Pennsylvania	0.095	Georgia	0.051
Kansas	0.109	Pennsylvania	0.099	Montana	0.083	Utah	0.051
Massachusetts	0.105	Kansas	0.096	Louisiana	0.069	South Carolina	0.050
South Carolina	0.101	South Carolina	0.093	Mississippi	0.067	Rhode Island	0.025
Montana	0.086	Montana	0.080	New Mexico	0.064	Minnesota	0.022
Rhode Island	0.036	Georgia	0.043	South Carolina	0.042	Montana	-0.001
Georgia	0.035	Rhode Island	0.036	Rhode Island	0.035	Vermont	-0.007
New Mexico	0.030	New Mexico	0.025	Wyoming	-0.004	Mississippi	-0.012
Wyoming	-0.008	Vermont	-0.011	Vermont	-0.010	Tennessee	-0.015
Vermont	-0.011	Wyoming	-0.017	Arizona	-0.017	Louisiana	-0.020
Oklahoma	-0.041	New Hampshire	-0.051	Georgia	-0.025	New Hampshire	-0.029
New Hampshire	-0.050	Oklahoma	-0.056	Oklahoma	-0.039	Oklahoma	-0.032
Michigan	-0.064	Arizona	-0.058	New Hampshire	-0.047	Iowa	-0.036
Alaska	-0.069	Alaska	-0.071	Alaska	-0.062	Wyoming	-0.038
Arizona	-0.071	Hawaii	-0.080	Hawaii	-0.071	Maine	-0.067
Maine	-0.083	Michigan	-0.085	Maine	-0.078	South Dakota	-0.070
Indiana	-0.084	Maine	-0.085	Indiana	-0.087	Illinois	-0.078
Hawaii	-0.088	Indiana	-0.100	Iowa	-0.088	Alaska	-0.079
Iowa	-0.103	Iowa	-0.114	Michigan	-0.105	New Mexico	-0.084
Arkansas	-0.117	Arkansas	-0.122	South Dakota	-0.114	Nevada	-0.086
Tennessee	-0.118	Tennessee	-0.122	Minnesota	-0.123	District of Columbia	-0.097
South Dakota	-0.124	South Dakota	-0.128	Arkansas	-0.128	Indiana	-0.114
Minnesota	-0.141	Minnesota	-0.149	Tennessee	-0.132	Hawaii	-0.117
District of Columbia	-0.153	District of Columbia	-0.152	Utah	-0.133	Michigan	-0.131
North Carolina	-0.163	North Carolina	-0.154	District of Columbia	-0.168	Connecticut	-0.136
Maryland	-0.174	Maryland	-0.173	North Carolina	-0.181	North Carolina	-0.137
Utah	-0.178	Utah	-0.178	Illinois	-0.207	Arizona	-0.157
Illinois	-0.181	Illinois	-0.180	Maryland	-0.208	Nebraska	-0.177
Ohio	-0.216	Connecticut	-0.226	Connecticut	-0.218	Texas	-0.179
Connecticut	-0.230	Ohio	-0.234	Washington	-0.220	Ohio	-0.185
Washington	-0.263	Washington	-0.258	Ohio	-0.234	Washington	-0.198
Texas	-0.295	Texas	-0.279	Texas	-0.277	Maryland	-0.199
Wisconsin	-0.332	Wisconsin	-0.348	Wisconsin	-0.329	Wisconsin	-0.211
Nebraska	-0.410	Nebraska	-0.415	Nebraska	-0.384	Arkansas	-0.220
California	-0.496	California	-0.426	California	-0.411	California	-0.292

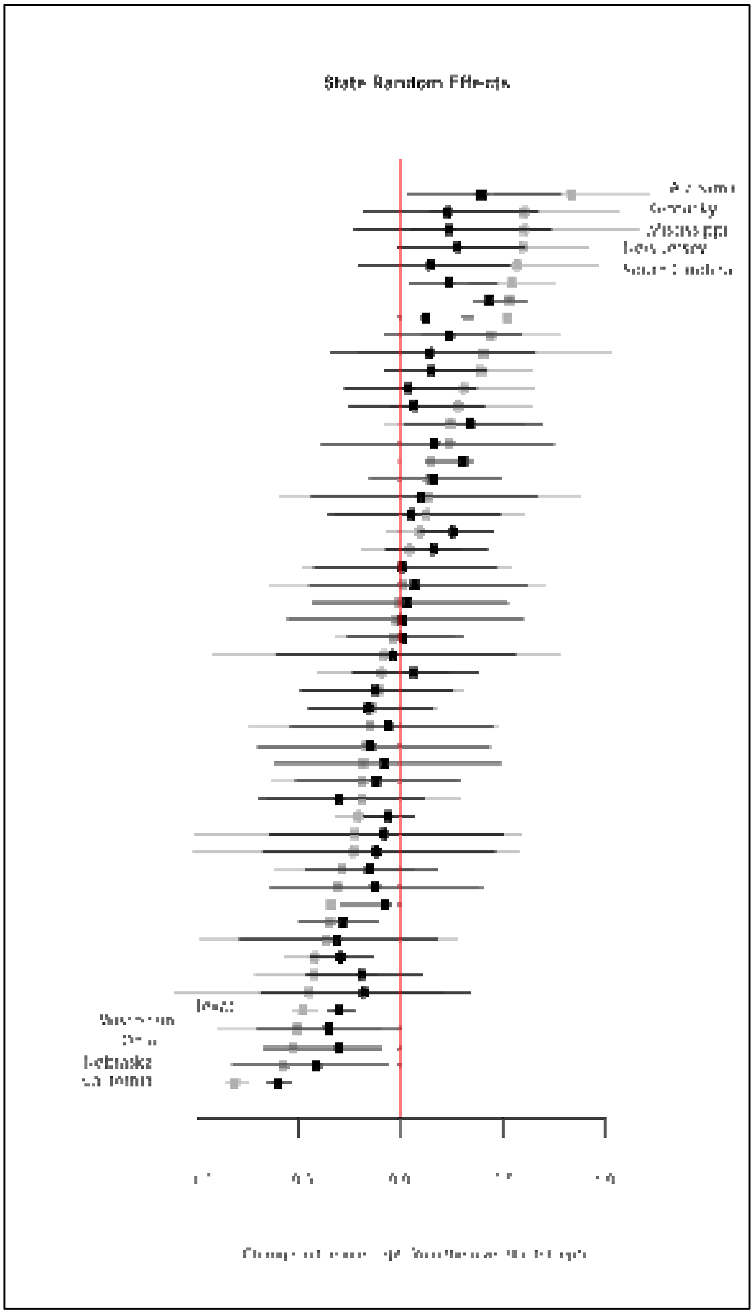

Figure 1. State Random Effects Estimates (Ordered) and 95% Confidence Intervals from Tables 3 and 4. Model 1 (gray) controls only for age and sex, and Model 2 (black) controls for age, sex, and immigrant generational status.

Figure 1 compares the ordered state random effects in Model 1 (gray) and Model 2 (black). For most states, the absolute value of the state's random effect estimate shrinks towards the overall mean of the state means (zero, in red) from Model 1 to Model

2. In Model 2, Alabama and New Jersey continue to have larger positive random effects than other states, but are now joined by Florida, Missouri, and Nevada (see Figure 2 and Table 4). These high and low deviations cannot be fully explained by compositional differences in the generational status of the Mexican origin population across states.

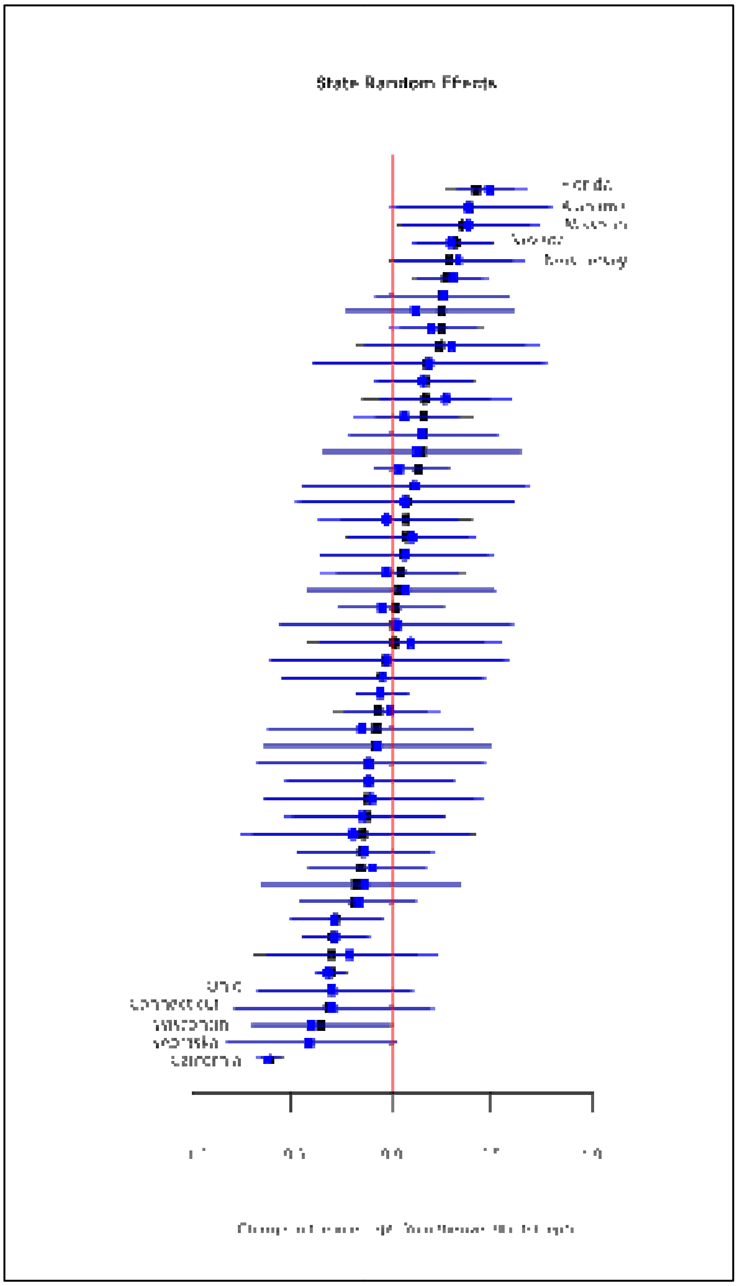

Figure 2. State Random Effects Estimates (Ordered) and 95% Confidence Intervals from Tables 3 and 4. Model 2 (black) controls for age, sex, and immigrant generation. Model 4 (blue) controls for all individual-level covariates.

The overall variance in the state intercepts is fairly stable across Models 2, 3, and 4 (approximately .9). Figure 2 contrasts the state random effects from Model 2 (black), which controls for age, sex, and immigrant generation, and Model 4 (blue), which controls for all individual-level covariates. This figure demonstrates that the state random effects are similar for both models. While factors such as parental education, family status, central city status, and mobility are significant predictors of school non-enrollment among the overall Mexican origin population, they do not substantially reduce between-state variation in non-enrollment above and beyond immigrant generational status. This could be due to a lack of variation in patterns of Mexican origin parental education, family status, and mobility across states, net of immigrant generational status.

In Models 5-7, I add state-level immigration history variables to the model that controls for all individual-level covariates (Model 4). I first control for percent foreign-born in the state in 1990, then for the percent foreign-born growth from 1990-2010, and then for the two variables together. These models yield surprising results. The percent foreign-born in the state in 1990 and the percent foreign-born growth rate in the state from 1990 to 2010 do not have significant effects on the overall likelihood of Mexican origin non-enrollment, net of compositional factors. Together, these variables do not substantially reduce the between-state variance in the log odds of non-enrollment. The state variance parameter decreases from .095 in Model 4, to .084 in Model 7. Thus, variables related to a state's immigration history are not significant predictors of non-enrollment among Mexican origin adolescents, and they do not explain much of the between-state variance in Mexican origin non-enrollment. Similarly, the percent NH Black peers in the state (Model 8) does not appear to significantly influence the likelihood of non-enrollment, nor does this variable noticeably reduce between-state variation in Mexican origin non-enrollment.

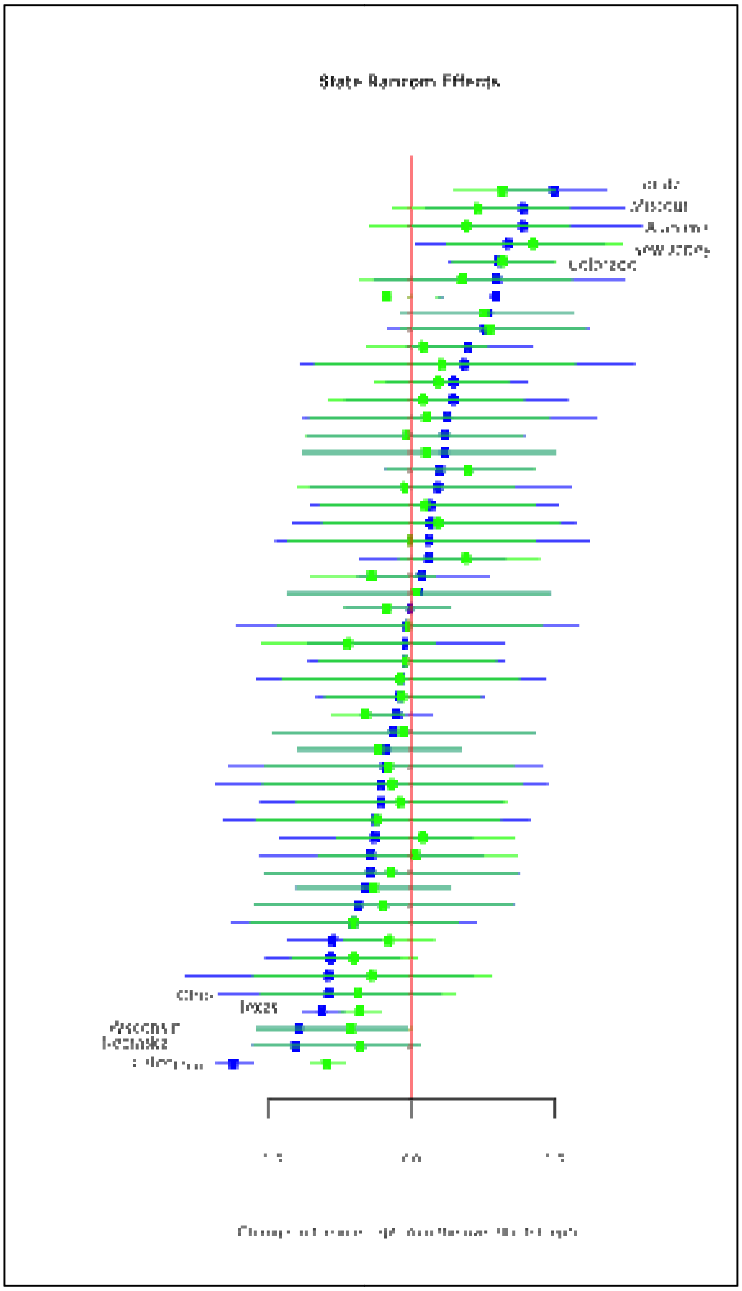

Figure 3. State Random Effects Estimates (Ordered) and 95% Confidence Intervals from Tables 3 and 4. Model 4 (blue) controls for all individual-level covariates. Model 9 (green) controls for all individual-level and state-level covariates.

The percent of NH White 15-17 year-olds in the state that are not enrolled in school is the only state-level characteristic that has a significant, positive effect on the likelihood of Mexican origin non-enrollment. Net of compositional characteristics, immigration history, and peer composition, Mexican origin adolescents who live in states with higher percentages of NH White peer dropouts are more likely to be non-enrolled in school. However, the level of NH Black non-enrollment in the state does not operate in the same way; the percent NH Black non-enrollment is not a significant predictor of Mexican origin non-enrollment.

Controlling for NH White peer non-enrollment and NH Black peer non-enrollment together reduces the between-state variance by a noticeable amount (from .080 in Model 8 to .056 in Model 9). Figure 3 also shows that controlling for all state-level covariates (green) shrinks the absolute values of the random effects parameters for most states towards the mean, to a greater extent than the model that only controls for individual-level characteristics (blue). However, the addition of state-level covariates does not improve the model fit. The best-fit model (the model with the lowest BIC) is Model 4, which only controls for individual-level predictors.

Overall, these results show that factors related to the composition of the Mexican origin population, particularly immigrant generational status, account for some of the between-state variation in Mexican origin non-enrollment. An assessment of state-level variables further reveals that the educational context of a state appears to influence both the likelihood of Mexican origin non-enrollment and between-state variance in non-enrollment. In contrast, variables related to a state's immigration history, such as the percent foreign-born living in the state in 1990 and the percent foreign-born growth rate in the state from 1990 to 2010, do not have significant effects on Mexican origin non-enrollment, and do not appreciably reduce between-state variation in Mexican origin non-enrollment, net of compositional factors. These findings suggest that the school dropout patterns of NH White adolescents within the state serve as key indicators of the overall quality of the education system. Some Mexican origin adolescents that are exposed to these poor-quality education systems are at greater risk of school dropout than their peers in other states.

Conclusion

The emergence of new immigrant destinations has coincided with a proliferation of studies seeking to compare immigrant outcomes across contexts. This wave of studies relies heavily on the use of destination typologies, which place destinations into categories based exclusively on variables related to immigration history. I have argued in this paper that the use of destination typologies prevents the effective generalization of results across studies. In this paper, I have attempted to demonstrate the utility of a multilevel approach to analyzing immigrant outcomes across destinations, by studying variations in levels of Mexican origin non-enrollment across states. My findings show that variables related to a state's immigration history do not influence between-state variation in non-enrollment to the same extent as individual-level compositional factors, such as immigrant generation, and the educational context within the state, as measured by the percent of NH White 15-17 year-olds who are not enrolled in school. These findings suggest that scholars should not automatically assume that a destination's immigration history is the most salient determinant of between-destination variations in outcomes relevant to immigrant assimilation, such as school non-enrollment.

I have advocated for the use of multilevel modeling in the study of variations in outcomes across immigrant destinations. However, multilevel modeling may not be appropriate for all circumstances. Multilevel models require the use of nested data. This type of data may not be available, and multilevel analysis may not be appropriate for the unit of analysis or dependent variable of interest. Still, I would argue that, even in standard OLS regression models, researchers should not begin the analysis by creating destination typologies, but rather should introduce variables related to immigration history into the models as covariates. In this way, researchers can evaluate whether immigration history variables play a significant role in predicting the outcome of interest relative to other factors.

There are several limitations to the analysis presented in this paper. First, I did not find that immigration history variables related to destinations (states) had significant effects on Mexican origin non-enrollment, nor on between-state variation in non-enrollment. This could be due to the fact that I measured immigration history using the presence of the foreign-born population within the state in 1990, and foreign-born growth rates from 1990 to 2010. These results may have been different if I had focused specifically on the presence and growth of the co-ethnic (Mexican origin) population within the state. The historical presence of co-ethnics may have a greater influence on outcomes such as school non-enrollment than the historical presence of all foreign-born individuals. Second, while I have highlighted variation in Mexican origin non-enrollment rates across states, the state may not be an important sphere of influence for immigrant origin individuals. Institutional arrangements at lower levels of geography may have a greater impact on the outcomes of immigrants and their families. Future analyses should attempt to measure contextual variables within smaller geographic units of analysis, such as the Public Use Microdata Area (PUMA) or county. Finally, Mexican origin adolescents living in California and Texas dominate the 2005-2009 ACS sample. This could suppress the overall level of variation in non-enrollment outside of these states. To circumvent this challenge, future work could divide these states into smaller geographic units, as suggested above, or omit these states from the analysis altogether.

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Appendix

Table Al. Mean Individual-level Characteristics of Mexican Origin, NH White, and NH Black 15-17 Year-olds, 2005-2009 ACS.

	Mexican Origin	NH White	NH Black
Demographics			
Age	16.0	16.0	16.0
Female (%)	48.4	48.6	49.8
Male (%)	51.6	51.4	50.2
Household Family Status			
No parents in HH (%)	8.9	4.6	12.1
Intact (Mother and Father) (%)	60.3	70.4	31.8
Mother, no Father (%)	24.3	18.4	49.6
Father, no mother (%)	6.6	6.6	6.5
Immigrant Status, Citizenship, Mobility			
1.25 Generation (%)	4.4	0.4	1.1
1.5 Generation (%)	8.7	0.9	2.0
1.75 Generation (%)	8.1	1.3	1.6
Native-born (%)	78.8	97.4	95.3
Non-citizen (%)	18.4	1.1	2.7
Recent mobility (in last year) (%)	13.9	9.4	16.9
Metropolitan Status			
Central City (%)	20.9	7.0	31.5
Non-metropolitan (%)	9.5	20.2	10.8
Other (other metro or not identifiable) (%)	69.6	72.8	57.7
Poverty Status			
Below Poverty (%)	25.9	9.4	29.8
1-2x Poverty Threshold (%)	32.3	14.5	26.8
2x + Poverty Threshold (%)	41.8	76.2	43.4
Highest Parental Educational Attainment			
No parental or householder record (%)	0.4	0.2	0.4
Less than HS (%)	40.6	4.8	14.4
HS Degree or GED (%)	25.8	22.4	31.3
Some College (%)	17.3	22.4	26.8
AA (%)	5.7	11.5	9.7
BA (%)	7.0	22.4	11.2
BA + (%)	3.2	16.3	6.1

*Percentages are weighted using the person weights provided by the IPUMS ACS dataset.

Table A2. State Characteristics, 1990 Census (5% microdata sample), 2005-2009 ACS, 2010 ACS

	Foreign Born (FB) Characteristics: 1990		Peer Composition (15-17 year-olds): 2005-2009			Educational Context: 2005-2009			
State	Percent Foreign Born: 1990	Percent FB Growth: 1990-2010	Percent NH White 15-17 Year-olds: 2005-2009	Percent NH Black 15-17 Year-olds: 2005-2009	Percent Latino 15-17 Year-olds: 2005-2009	Percent Adults (ages 25-64) with Less than a HS Degree: 2005-2009	Percent School Non-Enrollment Among NH White 15-17 year-olds	Percent School Non-Enrollment Among NH Black 15-17 year-olds	State Population Total: 2005-2009
Alabama	1.7	205.0	62.9	31.5	2.6	15.1	4.58	4.17	4,633,304
Alaska	5.8	97.1	57.8	3.2	5.6	6.4	4.69	11.76	683,142
Arizona	8.8	191.3	47.6	4.2	37.7	8.7	4.79	3.9	6,324,865
Arkansas	1.6	314.7	70.3	19.6	6.2	13.4	5.56	4.62	2,838,143
California	23.1	55.5	34.3	6.9	44.3	8.0	2.36	2.76	36,308,527
Colorado	5.5	210.9	65.6	4.6	23.6	6.1	3.77	4.06	4,843,211
Connecticut	11.5	60.3	68.5	11.3	14.8	5.8	2.18	5.17	3,494,487
Delaware	4.6	179.9	62.0	25.8	7.9	9.0	4.27	3.48	863,832
District of Columbia	10.8	39.4	11.0	76.9	8.9	10.0	0	6.34	588,433
Florida	15.0	120.9	52.9	20.3	22.1	9.6	4.69	4.84	18,222,420
Georgia	3.6	354.3	52.6	35.4	7.4	12.4	3.88	4.39	9,497,723
Hawaii	17.6	46.4	15.8	2.1	10.5	4.6	5.79	4.55	1,280,241
Idaho	3.6	197.3	81.9	0.4	12.9	7.7	3.72	4.76	1,492,573
Illinois	9.4	77.2	59.1	18.5	17.0	7.7	2.42	4.29	12,785,043
Indiana	2.3	170.5	80.6	10.2	5.4	10.6	4.14	5.31	6,342,469
Iowa	2.0	178.3	88.5	3.0	4.5	6.1	3.49	2.26	2,978,880
Kansas	3.2	165.2	77.6	6.7	10.5	6.4	2.71	5.21	2,777,835
Kentucky	1.4	246.8	85.6	9.0	2.5	14.9	4.43	4.51	4,252,000
Louisiana	2.6	80.7	54.8	38.5	3.1	16.0	4.68	5.26	4,411,546
Maine	4.0	24.0	91.8	1.5	1.9	6.9	4.15	10.3	1,316,380
Maryland	7.7	141.1	54.0	32.8	6.4	8.3	3.98	4.05	5,637,418
Massachusetts	11.7	61.6	74.4	7.3	11.6	5.5	2.61	4.93	6,511,176
Michigan	4.4	58.3	72.0	18.2	4.9	8.7	3.51	6.03	10,039,208
Minnesota	3.3	185.1	81.5	4.9	4.4	4.5	2.09	5.64	5,188,581
Mississippi	1.2	137.7	50.8	44.8	2.0	16.8	5.1	4.54	2,922,240
Missouri	2.1	148.9	77.9	14.3	3.5	10.5	4.53	5.76	5,904,382
Montana	2.4	44.8	82.6	0.6	3.3	6.8	6.28	6.72	956,257
Nebraska	2.3	237.4	81.1	5.5	9.2	5.3	1.95	3.23	1,772,124
Nevada	10.1	363.6	49.4	9.4	31.3	8.4	6.42	4.46	2,545,763
New Hampshire	4.6	63.1	92.0	1.1	3.1	6.9	2.7	0	1,315,419
New Jersey	15.2	76.6	58.9	15.5	17.2	6.3	2.31	4.27	8,650,548
New Mexico	6.4	137.2	30.8	2.4	52.0	10.3	4.92	2.76	1,964,860
New York	15.3	39.0	55.3	17.6	18.9	8.0	2.71	3.78	19,423,896
North Carolina	2.5	403.1	61.4	26.1	6.8	11.7	4.5	3.99	9,045,705
North Dakota	2.0	60.4	85.7	0.9	2.2	5.6	4.39	6.58	639,725
Ohio	2.9	74.8	78.8	14.4	3.0	9.9	3.28	3.98	11,511,858
Oklahoma	2.8	170.5	64.2	8.9	8.9	10.9	3.92	2.68	3,610,073
Oregon	5.7	155.7	76.1	2.0	13.4	7.0	4.66	0.74	3,727,407
Pennsylvania	4.1	89.7	76.8	13.3	6.0	8.3	3.85	3.82	12,516,596
Rhode Island	10.8	43.4	72.8	6.2	15.3	8.3	2.86	9.3	1,057,381
South Carolina	2.2	250.2	57.9	35.6	3.6	13.6	3.9	3.64	4,416,867
South Dakota	1.6	148.5	81.4	0.7	3.2	7.1	3.26	0	796,513
Tennessee	1.7	313.5	72.2	21.1	3.4	13.6	3.35	3.69	6,158,953
Texas	10.2	156.7	41.1	12.9	41.2	11.3	3.08	3.37	23,819,042
Utah	4.3	250.5	80.6	1.0	12.2	5.8	2.62	0.73	2,651,816
Vermont	4.0	52.1	93.8	1.1	2.0	6.6	3.51	7.69	620,414
Virginia	6.5	162.3	62.5	23.3	6.9	10.1	2.67	3.67	7,721,730
Washington	8.1	158.0	71.3	3.7	12.2	6.3	3.64	4.55	6,465,755
West Virginia	1.2	32.4	92.5	3.3	1.8	14.0	5.08	9.4	1,811,403
Wisconsin	2.9	108.2	80.1	8.1	6.1	6.8	2.52	7.12	5,599,420
Wyoming	2.4	87.1	85.1	1.2	8.1	5.8	4.92	0	523,949

Table A3. State Random Effects Estimates for Log Odds of Non-Enrollment, Mexican Origin 15-17 Year-olds, 2005-2009 ACS.

State	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Alabama	0.844	0.406	0.391	0.398	0.355	0.357	0.345	0.298	0.199
Alaska	-0.298	-0.113	-0.073	-0.090	-0.088	-0.059	-0.071	-0.062	-0.079
Arizona	-0.197	-0.049	-0.043	-0.050	-0.025	-0.071	-0.058	-0.017	-0.157
Arkansas	0.298	0.079	-0.019	-0.018	-0.060	-0.117	-0.122	-0.128	-0.220
California	-0.805	-0.593	-0.613	-0.617	-0.415	-0.436	-0.426	-0.411	-0.292
Colorado	0.110	0.275	0.325	0.313	0.298	0.269	0.268	0.307	0.325
Connecticut	-0.353	-0.303	-0.273	-0.286	-0.259	-0.230	-0.226	-0.218	-0.136
Delaware	0.419	0.156	0.116	0.134	0.122	0.120	0.117	0.100	0.061
District of Columbia	-0.156	-0.135	-0.171	-0.183	-0.170	-0.153	-0.152	-0.168	-0.097
Florida	0.539	0.438	0.471	0.504	0.595	0.545	0.578	0.542	0.324
Georgia	0.551	0.254	0.179	0.204	0.171	0.035	0.043	-0.025	0.051
Hawaii	-0.441	-0.167	-0.123	-0.125	-0.092	-0.038	-0.080	-0.071	-0.117
Idaho	0.152	0.174	0.243	0.275	0.246	0.247	0.238	0.275	0.262
Illinois	-0.413	-0.284	-0.242	-0.273	-0.241	-0.131	-0.180	-0.207	-0.078
Indiana	-0.125	-0.145	-0.099	-0.087	-0.125	-0.034	-0.100	-0.087	-0.114
Iowa	-0.175	-0.107	-0.100	-0.106	-0.131	-0.133	-0.114	-0.088	-0.036
Kansas	-0.083	0.077	0.116	0.109	0.079	0.109	0.096	0.116	0.205
Kentucky	0.612	0.244	0.311	0.305	0.267	0.249	0.241	0.247	0.184
Louisiana	0.027	0.021	0.096	0.102	0.078	0.132	0.119	0.069	-0.020
Maine	-0.217	-0.107	-0.089	-0.105	-0.103	-0.033	-0.085	-0.078	-0.067
Maryland	-0.177	-0.290	-0.201	-0.200	-0.189	-0.174	-0.173	-0.208	-0.199
Massachusetts	0.006	0.046	0.079	0.077	0.094	0.105	0.107	0.109	0.102
Michigan	-0.416	-0.178	-0.157	-0.156	-0.176	-0.054	-0.085	-0.105	-0.131
Minnesota	-0.088	-0.113	-0.118	-0.139	-0.159	-0.141	-0.149	-0.123	0.022
Mississippi	0.610	0.254	0.112	0.124	0.098	0.126	0.115	0.067	-0.012
Missouri	0.260	0.358	0.412	0.398	0.354	0.396	0.378	0.369	0.238
Montana	0.026	0.084	0.081	0.071	0.059	0.086	0.080	0.083	-0.001
Nebraska	-0.566	-0.402	-0.413	-0.401	-0.416	-0.410	-0.415	-0.384	-0.177
Nevada	0.163	0.322	0.313	0.301	0.336	0.116	0.155	0.184	-0.086
New Hampshire	-0.213	-0.071	-0.063	-0.062	-0.060	-0.050	-0.051	-0.047	-0.029
New Jersey	0.606	0.293	0.303	0.344	0.413	0.399	0.420	0.401	0.431
New Mexico	-0.332	-0.060	-0.023	0.001	-0.001	0.030	0.025	0.064	-0.084
New York	0.404	0.166	0.109	0.070	0.195	0.178	0.216	0.189	0.200
North Carolina	0.528	0.139	0.052	0.044	0.000	-0.153	-0.154	-0.181	-0.137
North Dakota	0.257	0.180	0.193	0.193	0.180	0.180	0.177	0.171	0.115
Ohio	-0.517	-0.292	-0.263	-0.286	-0.307	-0.216	-0.234	-0.234	-0.185
Oklahoma	-0.023	0.025	-0.023	-0.041	-0.076	-0.041	-0.056	-0.039	-0.032
Oregon	0.057	0.177	0.148	0.157	0.146	0.166	0.160	0.199	0.106
Pennsylvania	0.142	0.066	0.042	0.078	0.061	0.111	0.099	0.095	0.056
Rhode Island	-0.004	0.022	0.030	0.034	0.035	0.036	0.036	0.035	0.025
South Carolina	0.578	0.162	0.124	0.155	0.120	0.101	0.093	0.042	0.050
South Dakota	-0.170	-0.067	-0.140	-0.141	-0.145	-0.124	-0.128	-0.114	-0.070
Tennessee	0.327	0.053	-0.013	-0.019	-0.059	-0.118	-0.122	-0.132	-0.015
Texas	-0.469	-0.291	-0.299	-0.309	-0.266	-0.235	-0.279	-0.277	-0.179
Utah	-0.279	-0.141	-0.131	-0.126	-0.144	-0.178	-0.178	-0.133	0.051
Vermont	-0.073	-0.024	-0.013	-0.013	-0.013	-0.011	-0.011	-0.010	-0.007
Virginia	0.448	0.256	0.255	0.264	0.258	0.238	0.256	0.225	0.281
Washington	-0.336	-0.271	-0.282	-0.279	-0.262	-0.253	-0.258	-0.220	-0.198
West Virginia	0.149	0.113	0.131	0.124	0.111	0.127	0.122	0.120	0.060
Wisconsin	-0.498	-0.343	-0.363	-0.389	-0.410	-0.332	-0.348	-0.329	-0.211
Wyoming	-0.137	-0.046	-0.037	-0.035	-0.049	-0.038	-0.017	-0.004	-0.038