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THE LOCATION CHOICE OF EMPLOYMENT-BASED IMMIGRANTS AMONG U.S. METRO AREAS*

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ABSTRACT. This paper examines the initial location choice of legal employment-based immigrants to the United States using Immigration and Naturalization Service data on individual immigrants, as well as economic, demographic, and social data to characterize the 298 metropolitan areas we define as the universal choice set. Focusing on interactions between place characteristics and immigrant characteristics, we provide multinomial logit model estimates for the location choices of about 38,000 employment-based immigrants to the United States in 1995, focusing on the top 10 source countries. We find that, as groups, immigrants from nearly all countries are attracted to large cities with superior climates, and to cities with relatively well-educated adults and high wages. We also find evidence that employment-based immigrants tend to choose cities where there are relatively few immigrants of nationalities other than their own. However, when we introduce interaction terms to account for the sociodemographic characteristics of the individual immigrants, we find that the estimated effects of location destination factors can reverse as one takes account of the age, gender, marital status, and previous occupation of the immigrants.

1. INTRODUCTION

The role of immigrants continues to grow economically and demographically, with one-half of the increase in the U.S. population in the past decade due to the entry of foreign-born persons. This is widely recognized and is a

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subject of intense national debates. However, the regional distribution of immigrants is discussed much less, and local economic development and social services officials have only a small body of literature to consult on immigration-related challenges. They can benefit from learning more about immigration determinants as they pursue efforts to stem or stimulate regional immigration. At the national level, elected officials and immigration specialists in the federal government can usefully learn more about the diverse, and probably unintended, regional impacts of its immigration policy actions. Immigrants themselves often have limited information about settlement choices available in the United States and can also benefit from our findings. The results of this and other studies of location decisions by immigrants can have predictive value and thus can be used in helping regional economic forecasts.

Immigrants' location choices in a host country result from an interaction of their individual characteristics, such as age, marital status, or professional occupation, and characteristics of potential locations, such as the size of an existing immigrant community or the strength of a local economy. Much of the previous research on immigrant settlement analyzed individual and place characteristics separately, focusing on either group of factors. In this paper, we emphasize the analysis of *simultaneous* interactions of key individual and place characteristics of the immigrant location choice decision. We believe that this approach allows for a more accurate discussion of settlement patterns of immigrants and thus might be of particular interest for policymakers at the federal and local levels. We find that taking account of the interaction of individual and place characteristics often has a great impact on estimated coefficients in location choice models.

Unlike most previous investigators, we examine immigrant location decisions for cities rather than for states. A priori, one should obtain a richer and more precise understanding of the importance of location factors by examining 298 metropolitan areas rather than only 50 states. Unlike states, metropolitan areas are good proxies for important concepts in economic geography like community, labor market, and housing market. For example, it seems quite crude to treat the place characteristics of California as uniform given the wide variation in topography, climate, industrial structure, and human capital one observes among metros like San Diego, Oakland, and Bakersfield. Moreover, immigration in the United States continues to be almost exclusively an urban phenomenon. In 2000, 95 percent of all foreign-born in the United States resided in metropolitan areas, while 55 percent resided in the six "gateway cities" of Los Angeles, New York, Miami, San Francisco, Chicago, and Washington-Baltimore, which comprise only 23 percent of the U.S. population (Camarota, 2001).

Finally, in our analysis we focus on employment-based immigrants, those who settle in the United States based on the strength of their professional skills. Among the four major categories of legal immigrants (immediate relatives of U.S. citizens, other family-based immigrants, employment-based

immigrants, and refugees), employment-based immigrants are perhaps of most interest for location choice analysis. Employment-based immigrants have greater freedom of settlement and are found to be sensitive to a wider range of socioeconomic characteristics of potential locations (Bartel, 1989; Buckley, 1996; Zavodny, 1998; Jaeger, 2000). In contrast, the location choices of immediate relatives of U.S. citizens and other family-based immigrants are largely predetermined by their sponsoring family-members. Refugees are settled in the United States by refugee agencies, and hence their settlement pattern is largely a function of policies at the State Department and the interest of local communities in placing more refugees from a particular country.

2. DETERMINANTS OF MIGRATION

In a survey of primary determinants of internal U.S. migration, Greenwood (1985) classifies them into two categories: characteristics of the individual or family unit and the differential characteristics of the sending and receiving regions. Individual traits include age, gender, marital status, health, education, accumulated job skills, and labor force status. Place characteristics include climate and topography, local labor market conditions, real estate market conditions, state and local taxes, and availability of public goods. Greenwood points out that some of these factors are interrelated. For example, an attractive climate will lead to lower wages and higher housing prices, *ceteris paribus*, as workers receive offsetting nonpecuniary income from the high local quality of life (see also Bloomquist, Berger, and Hoehn, 1988). A large literature has developed that quantifies the importance of these factors in explaining the movement of people from one state or city to another.

Unlike intracountry movements of people, intercountry movements are subject to a high degree of government regulation and often are constrained by significant physical and information barriers. However, for immigrants who are either already living in the United States or accepted for arrival, location choice inside the country can be viewed as a function of their personal characteristics and of the characteristics of places in the United States. The immigrant's desire and ability to improve his or her condition depends upon age, gender, marital status, nationality, legal status, education, and other factors. The "pull" of different locations depends on the strength and nature of the attraction determined by each place's economy, demography, and amenities. Figure 1 summarizes some of the primary individual and place characteristics that have been mentioned in the literature.

With regard to data used to analyze the location choices of immigrants, existing studies fall into two groups. Some focus on the flow of new immigrants and rely mainly on Immigration and Naturalization Service (INS) data, while others analyze settlement and resettlement patterns of immigrants already living in the United States and use decennial census data. The annual INS compilations contain individual records on each alien legally admitted for

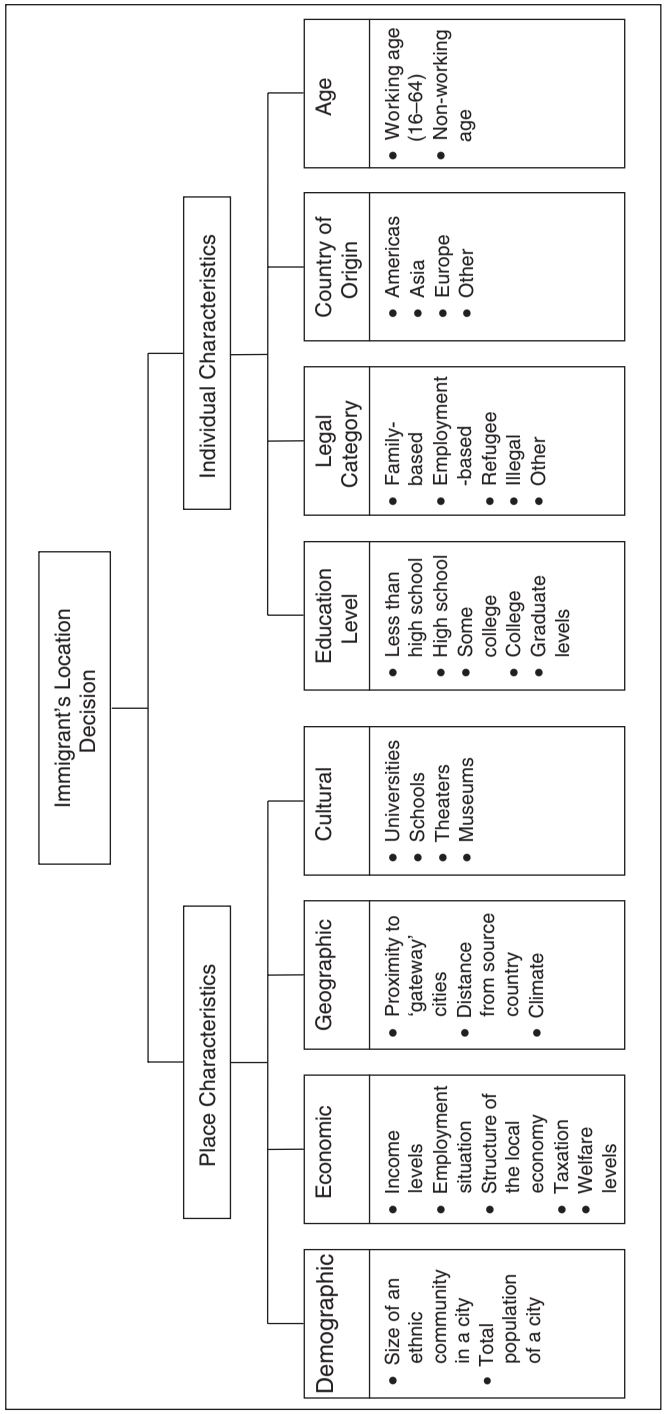

FIGURE 1: Location Choice Factors for Immigrants to the United States.

permanent residence. The records include data on age, gender, countries of birth and last residence, port of entry, class of admission (refugee, family, and employment), declared occupation, and zip code of intended residence. In contrast to this, census data contain more attributes, but are based on surveys and are available in full only once every ten years. Each approach and each data set has its advantages and disadvantages (for comparisons between census and INS data sets, see Newbold, 2000).

While decisions of immigrants about their settlement come as a result of interaction between their own characteristics and those of potential locations, many studies of immigrant location decisions do not explicitly consider this interaction and focus instead on either immigrant characteristics or those of potential locations. There are, however, some important exceptions in the literature. Bartel (1989), using census data, disaggregated immigrants into three ethnic groups, three cohorts based on arrival time to the United States, and three levels of education. Immigrant location choices in her study are considered for the 25 largest metro areas and 4 geographical zones covering the rest of the country. She found significant interactions between the education levels of immigrants and a measure of ethnic concentration—education weakened the enclave effect—but not with other place characteristics. Jaeger (2000) uses INS data to analyze the location choices of different legal categories of new immigrants to the United States in 1991. In contrast to Bartel, he found immigrant location choices to be strongly sensitive to economic characteristics of locations, such as labor market conditions. Davies, Greenwood, and Li (2001) examine state-to-state migration patterns over 11 years, and while stating that ideally a model should include characteristics of the individuals, were forced for computational reasons to estimate a model that includes only characteristics of the states. Other studies of immigrant location choice, where interaction of immigrant and location characteristics is explicitly addressed include those of Newbold, who studied location choices of immigrants in Canada (1996) and in the United States (1999). In both of these papers, the focus is on patterns of secondary migration of immigrants. Newbold's findings, based on census data and a multinomial logit model, largely confirm a high sensitivity of immigrant location choices to ethnic concentration and economic factors. His results for the United States indicate variations of settlement behavior among different subgroups of immigrants. The author points out, however, that his investigation of such variations is limited by sample size issues (see Newbold, 1999, p. 264).

In most of the existing studies, location choices of immigrants are considered at the state level. In the state-level studies by Buckley (1996), Zavodny (1998), and Dodson (2001), immigrant flow is differentiated by legal categories, and Zavodny differentiates additionally by five national origin groups. In Jaeger (2000), location choice is represented by 35 metropolitan areas, while the immigrants are categorized into 14 groups based on their region of origin. Other studies use even larger geographical areas than states, such as that by Belanger and Rogers (1992), where location choices of immigrants are

limited to four U.S. regions. Kritz and Nogle (1994), who provide the most detailed classification of personal characteristics of immigrants (national origin, sex, age, education, time in the United States, and self-employment status), limit immigrant location choices to just two: the in-state and out-of-state migration options.

Other than data limitations, significant computational difficulty is one of the main reasons for a shortage of immigrant location choice studies that include more comprehensive and simultaneous analysis of multiple attributes of individual immigrants and multiple characteristics of potential destinations. Estimating relevant multinomial logit models turns out to be a daunting econometric and computational problem, given that one has to process data on tens or hundreds of thousands of immigrants of widely varying traits choosing among hundreds of different localities. We have overcome this hurdle by using a random sampling technique, generating a location choice set of 10 metropolitan areas for each immigrant. McFadden (1978) has demonstrated that this approach yields consistent estimates.

The design of our study is therefore different from previous research in three aspects. First, we use more detailed disaggregations, including 10 national origins, 298 Metropolitan Statistical Areas (MSAs), 4 personal characteristics of each immigrant, and 8 characteristics of each place. Second, we use employment-based immigrants, as opposed to all immigrants, as these are more sensitive to both ethnic and socioeconomic characteristics of locations. Finally, we attempt to analyze the simultaneous interaction of personal and place factors on immigrant location choice in more detail than other studies.

We have included maps (see Figure 2) of employment-based immigrants from four countries—El Salvador, India, Japan, and the United Kingdom—to give the reader a feel for the variation in settlement patterns by nationality and metropolitan area. The maps show each metro's percentage share of immigrants of particular nationalities entering the United States in 1995. Immigrants from India and the United Kingdom have settled in a relatively ubiquitous way around the United States, with a strong presence in West Coast cities, the Plains, the upper Midwest, the Southeast, and in all the major cities along the eastern seaboard. In contrast, immigrants from El Salvador and Japan are much more geographically concentrated.[1] Salvadorans have clustered almost exclusively in large coastal cities. Japanese have settled most intensely in West and East Coast cities, but also have a presence in the upper Midwest.

It is well established that immigrants, particularly those with little education or poor English-speaking skills, tend to live in large enclaves of their

[1]The issue of how to define and measure "concentration" for a particular national or ethnic group in the era of instant communication is a subject of debate in the immigration literature (see, for example, Zelinsky and Lee, 1998). In this paper, we are limiting our analysis to the traditional measure of settlement concentration at the level of metro areas. The number of foreign-born persons living in a metro area is a good proxy for geographic concentration for most nationalities (Izyumov et al. 2002).

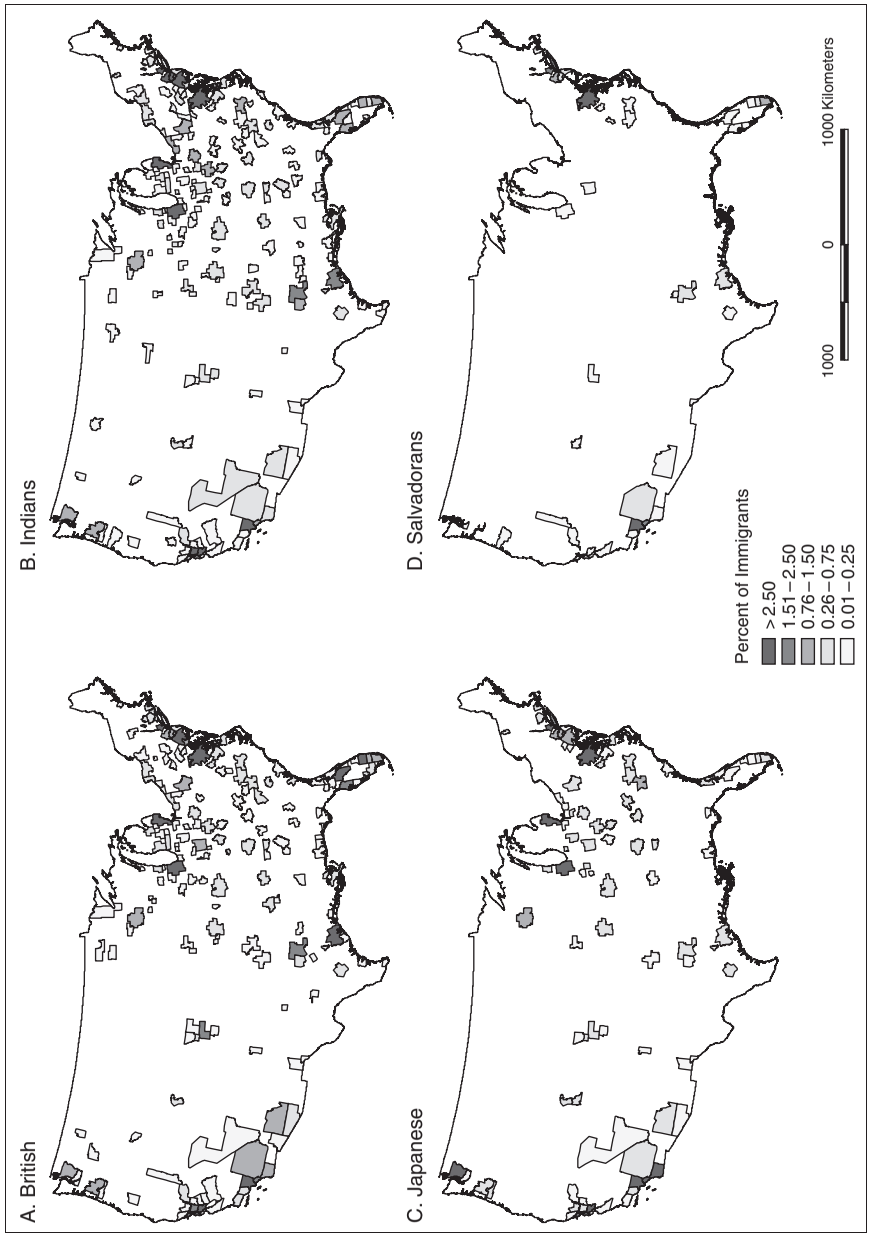

FIGURE 2: Spatial Distribution of 1995 Legal Employment-Based Immigrants to the United States from (A) United Kingdom, (B) India, (C) Japan and (D) El Salvador: Percentage of Immigrants of Each Nationality Settling in Each Metro Area.

compatriots. This is true for both the already settled immigrants (stocks) and for the new arrivals (flows) (see Smith and Edmondston, 1997; Borjas, 1999; Camarota, 2001). As an illustration of this effect, we plotted the 1990 immigrant stock against the 1990–1998 immigrant flow to U.S. metropolitan areas (see Figure 3), excluding the two largest—Los Angeles and New York—so the scale allows one to see many cities. Clearly, there is high positive correlation between stocks and flows. Indeed, the six gateway cities that comprise 70 percent of all foreign-born persons continue to gain the bulk of new immigrants due to a "greenhouse effect."[2] Bartel (1989), studying the location of working-age male immigrants, as revealed in the 1980 Census, confirmed this immigrant concentration trend and also provided estimates of the importance of local economic conditions and public assistance. Bartel and Koch (1991) used the same data set to examine the secondary migration of immigrants and found a continuing strong locational effect of the ethnic concentration. Later studies further confirmed these findings (see Kritz and Nogle, 1994; Allen and Turner, 1996; Newbold, 1996; Zavodny, 1998; Borjas, 1999; Newbold, 1999; Dodson, 2001; Gross and Schmitt, 2003).

More detailed investigation of the location choice of immigrants from different countries has found that the better-educated immigrants tend to disperse more widely than their less-educated compatriots. Presumably higher education

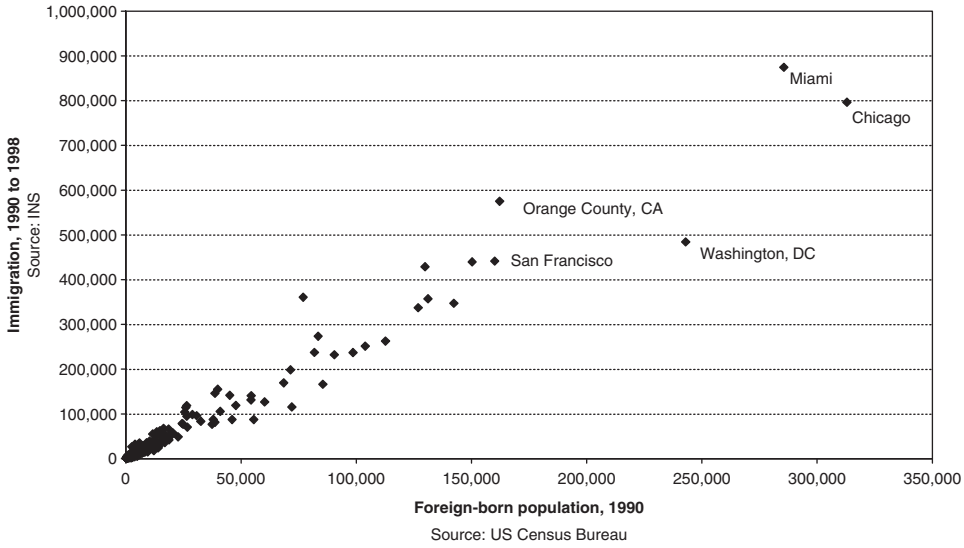

FIGURE 3: Immigration vs. Size of Foreign-Born Population in 300 MSAs, Excluding New York and Los Angeles.

[2]In the 1990s, this pattern was not as distinct as in the 1970s and 1980s since relatively more immigrants started to settle in inland cities and states (see, for example, Camarota and Keeley, 2001; Fix, Zimmerman, and Passel, 2001).

allows new immigrants to be less dependent upon the safety networks provided by ethnic communities (see Bartel, 1989; Dunlevy, 1991; Kritz and Nogle, 1994; Newbold, 1996, 1999; Zavodny, 1998; Frey and DeVol, 2000; Jaeger 2000; Izyumov et al. 2002). It has been further established that the secondary migration of foreign-born persons does not deviate from this pattern of settlement and, if anything, reinforces it. When secondary migration takes place, more educated immigrants tend to move within the United States in response to job opportunities, and the less educated ones tend to resettle in cities with larger ethnic communities (Bartel and Koch, 1991; Kritz and Nogle, 1994; Newbold, 1996, 1999). We expect that settlement patterns of employment-based immigrants should resemble those of more-educated immigrants in general. In particular, we expect settlement choices of the highest skilled among employment-based immigrants (professionals) to be least dependent upon ethnic enclaves. We also expect to find that, in keeping with the general migration literature, younger, male, unmarried, and professional workers would be most aggressive in seeking places with the highest pecuniary and nonpecuniary returns.

The role of the employer in the location choice of employment-based immigrants is not well understood. Employers often effectively act as sponsors, hiring foreign-born persons on a temporary basis while they seek a permanent immigrant status. For example, the H-1B visa program, whereby foreigners with special skills are expeditiously processed by the INS, explicitly requires employer sponsorship, and many large firms in the United States have used this channel to bring in talented software, medical, research, and other professionals. The demand for labor by these firms reflects growth in certain industries and regions, accompanied by a perceived shortage of specialty workers (for a given wage rate). However, potential immigrants must still be willing and able to live in the communities for the employers to be successful at hiring. Thus, we do expect place characteristics to matter for employment-based immigrants.

3. MODEL SPECIFICATION AND ESTIMATION METHOD

We postulate that an immigrant, characterized by certain personal and family traits, seeks to maximize utility through the choice of location in the United States. Following Bartel (1989), Dunlevy (1991), Kritz and Nogle (1994), Frey et al. (1996), Newbold (1996, 1999), Kanaroglou and Ferguson (1998), and Jaeger (2000), we use a multinomial logit framework as a way to model a utility maximizing immigrant in a discrete choice situation. The multinomial logit model is a popular framework for estimating the determinants of location choice for immigrants and migrants. In Kanaroglou and Ferguson (1998), for example, location choice probabilities were estimated and mapped for eight migrant types, where a type was defined to be a combination of binary characteristics for the largest groups of migrants in Canada. For example, the first type spoke only English, was a return migrant, and headed a multiperson household.

Hence, the authors used combinations of dummy variables to characterize groups, as opposed to measuring continuously each individual's characteristics (e.g., years of education). Moreover, they only observe the physical location choices of immigrants and do not attempt to measure the characteristics of the places and the pull effect those characteristics have on individuals.

In our modeling framework, we test two utility specifications. First, we consider a utility maximizing immigrant (i) who selects a MSA (j) based solely on a linear combination of characteristics (Zs) describing potential metro locations. The utility function (U_{ij}) is written as

$$U_{ij} = \sum_{k=1}^{K} \beta_k Z_{kj} + \varepsilon_{ij} \tag{1}$$

where the βs are coefficients to be estimated and ε_{ij} is a randomly distributed error term. Next, we test a more complex specification of utility in which *both* characteristics of MSAs and characteristics of immigrants are included. This second specification is possible through the introduction of interactions between the two types of characteristics. The utility function is written as

$$U_{ij} = \sum_{k=1}^{K} \beta_k Z_{kj} + \sum_{k=1}^{K} \sum_{l=1}^{L} \lambda_{kl} Z_{kj} X_{li} + \varepsilon_{ij} \tag{2}$$

where the Xs are characteristics of immigrants specified as dummy variables and the λs are interaction coefficients to be estimated. For both specifications, immigrant i chooses to locate in MSA m such that

$$U_{im} > U_{ij}, \quad \forall j,\ j \neq m$$

For simplicity, the utility functions specified in (1) and (2) can be rewritten as

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where V_{ij} is the systematic component of utility that can be measured by the analyst. If the random error term, ε_{ij}, is assumed to be independent and identically distributed (i.e., IID) then the probability that immigrant i chooses location j from among the MSAs is given as

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{j=1}^{J} e^{V_{ij}}} \tag{3}$$

which is the familiar multinomial logit model. The parameters (i.e., βs and λs) are obtained by maximizing the log-likelihood function

$$L^* = \sum_{i=1}^{I} \sum_{j=1}^{J} D_{ij} \log P_{ij}$$

where

$$D_{ij} = \begin{cases} 1 & \text{if immigrant } i \text{ chooses to locate in MSA } j, \\ 0 & \text{otherwise.} \end{cases}$$

As mentioned previously, the universal choice set of locations considered in our work consists of 298 MSAs in the United States. Researchers have noted that problems such as ours, which involve a large number of alternatives, are computationally expensive and thus, more often than not, prohibitive (see Ben-Akiva and Lerman, 1985; Train, 1993). This is perhaps one of the primary reasons why previous studies of the location choices of immigrants have focused on aggregate alternatives such as states (see, for example, Buckley, 1996; Zavodny, 1998; Dodson, 2001) or a relatively small number of cities (see, for example, Bartel, 1989; Jaeger, 2000).

Ben-Akiva and Lerman (1985) and Train (1993) state that this problem can be overcome by assuming an IID structure for the random error terms across alternatives. This IID structure gives rise to an important property of the multinomial logit model, that is, the independence from irrelevant alternatives (IIA) property. This property states that for a specific individual the ratio of the choice probabilities of any two alternatives in the choice set is unaffected by the systematic utilities of any other alternatives in the choice set. In other words, alternatives are assumed to be independent from one another. This property suggests that alternatives are inherently unique due to factors both observed by the analyst and factors that are unobserved. More importantly, they are viewed as unique by decision makers. If the IIA property does not hold, then an alternative to the multinomial logit model, such as the multinomial probit model, must be used. The latter model is not subject to violations of the IIA property because an IID structure for the random error terms is not assumed. The multinomial probit model is, however, computationally intensive because it requires the solution of a multidimensional integral to evaluate choice probabilities (Ben-Akiva and Lerman, 1985). For this reason alone, it cannot be applied to our problem involving 298 alternatives.

Instead, we assume an IID structure for the random error terms across alternatives. For each decision maker, we then draw a subset of nine alternatives from the universal choice set and add it to the chosen alternative. The multinomial logit model of location choice shown in Equation (3) is estimated based on a choice set of 10 alternatives for each decision maker. Ben-Akiva and Lerman (1985) describe several approaches for drawing a subset of alternatives from the universal choice set. We employ the simplest of these approaches, that is, drawing randomly some alternatives from the universal choice set and adding them to the chosen alternative. McFadden (1978) has shown that this approach to restricting the number of alternatives in the choice set, thus making problems involving large numbers of alternatives computationally tractable, yields consistent parameter estimates. The IIA property of the multinomial logit model can be exploited to simplify an otherwise computationally expensive undertaking, and the approach has been used

in several recent endeavors involving destination choice. Simma, Schlich, and Axhausen (2001), for example, use the approach to model the destination choice for Swiss leisure trips, whereas Pozsgay and Bhat (2002) use the approach to model the destination choice for home-based recreational trips in the Dallas-Fort Worth metropolitan area. In both studies, a random sample of nine alternatives from the universal choice set was added to the chosen alternative for each decision maker.

Ben-Akiva and Lerman (1985) point out that the IIA property is less likely to be violated if characteristics of decision makers are included in the model specification. We account for such characteristics in the second specification of our model as shown in Equation (2). At an early stage of our research, we also tested for violations of the IIA property for the specification shown in Equation (1). As noted, this specification considers only characteristics of the MSAs. For this task, we estimated a series of models for specific immigrant groups in which all 298 alternatives in the universal choice set were included in each immigrant's choice set (see Coomes, Scott, and Izyumov, 2002). As LIMDEP 7.0 (Econometric Software, 1998) was unable to estimate multinomial logit models involving more than 75 alternatives, a program was written in GAUSS 5.0 (Aptech Systems, 2002) for performing the task. Next, we estimated a series of models using the sampling procedure described above. Appendix A contains the parameter estimates for two immigrant nationalities: Indians and Taiwanese. As shown, the parameter estimates are very similar, suggesting that our approach does not appear to violate the IIA property of the multinomial logit model. Based on this finding, we proceeded to use LIMDEP 7.0 to estimate the models presented in Section 5.

4. DATA AND VARIABLES

We estimate separate models for each of the largest 10 nationalities of employment-based immigrants. More specifically, only immigrants aged 16 to 64 declaring a metropolitan area zip code as their initial place of residence in fiscal year 1995[3] are selected for analysis. We include four binary variables to characterize each immigrant—gender (1 if male, 0 if female), age (1 if immigrant is less than 40 years old; 0 otherwise), marital status (1 if immigrant is married; 0 otherwise), and professional status (1 if immigrant is employed as a professional; 0 otherwise). These sociodemographic characteristics are summarized by nationality in Appendix B. The professional status variable was

[3]We chose 1995 for this analysis for two reasons. First, because of the large number of observations, we needed to test the model using a single year before expanding to all the years of the decade. It turned out to be so demanding computationally to estimate the model for one year that we have postponed extending it to the other years. Second, employment-based immigrants tend to live and work in the United States for several years before they become legal permanent residents and therefore are, in fact, in the United States for several years before they are counted as new legal immigrants in the INS database. Hence, it is reasonable to analyze 1995 INS data on immigrants with 1990 Census data on foreign-born residents and the 1990 to 1995 growth in jobs by MSA.

constructed from self-reported immigrant occupation data. Eighteen of the twenty-seven occupations listed in the INS coding would require formal education at the bachelors level or above in the United States, and account for two-thirds of all the legal employment-based immigrants in 1995. Appendix C describes how we dealt with the many measurement issues associated with the INS data, including residency, admission class, time lags, and geocoding for the immigrant records.

We include eight place variables, entered as continuous measures. The number of foreign-born persons of the same nationality living in each metro area in 1990 is included to test for the importance of the enclave effect (Enclave). Enclaves generally are understood as compact settlements of immigrants living in close proximity to each other. However, the total number of immigrants of the same nationality seem to capture the "ethnic networks" effect fairly well. Izyumov et al. (2002) show that the number of foreign-born persons in a metro is a good proxy for enclaves, as a majority of new immigrants from most countries live in a small number of postal zip codes of the major gateway cities of the United States. In Chicago, for example, 47 percent of Chinese immigrants reported residence in but 10 of the metros' 381 zip codes. In addition, in the new age of instant communications, the strength of ethnic networks in a given metro area can be easily maintained without physical proximity of immigrants (for a discussion of the "heterolocalism" of modern immigration, see Zelinsky and Lee, 1998). According to the literature, the enclave effect should have a positive sign. However, employment-based immigrants may be less tied to their co-ethnics and the community benefits of the enclave as they are generally moving to a place where they have already arranged employment. We also include a measure of diversity (Diversity) to test whether there is a foreign-born population effect independent of the immigrant's nationality. This is calculated by subtracting the number of foreign-born residents of the immigrant's nationality from the total foreign-born population of the metro area in 1990. We expect this variable to take either a positive or negative sign, depending upon the propensity of immigrants from different nationalities to interact with each other. Also, we include the total 1990 population of the metro area (Urbanization) as a measure of the scope and scale of services and job opportunities available in each place. We expect this urbanization variable to take a positive sign.

We include the 1990 college attainment rate (College) of the metro adult population as a measure of the availability of professional jobs, and expect this to take a positive sign. We expect climate (Climate) to also affect the location decision of employment-based immigrants. We measure climate using the index produced by Savageau (2000). The index ranges from 1 (Rochester, Minnesota) to 100 (Santa Barbara, California), where metros are penalized for extreme temperatures, snow, seasonal swings, and hazardous weather. For metros not listed in *Places Rated Almanac*, we assigned the weather index value of the closest listed metro. Similarly, we expect higher wages to attract more immigrants, and we measure this by the 1995 average annual

earnings per job in each metro area. This is taken from the U.S. Bureau of Economic Analysis (2002) historical data set, and is calculated by dividing the total wages, salaries, proprietor's income, and other labor income by the total number of full- and part-time jobs in each metro. Finally, we include the percentage job growth over the previous five years, 1990 to 1995, as an indication of the general strength of each metro economy. We decomposed the job growth into that contributed from the goods-producing industries (Job Growth, Goods Industries) versus the service producing industries (Job Growth, Service Industries). As a measure of service sector job growth, we calculated the net growth in the following industries: finance, insurance, real estate, services, and government. The goods-producing industries were taken to be the remaining industries, which include agriculture, mining, manufacturing, transportation, and utilities. All place variables were scaled to similar magnitudes, as required for the multinomial logit procedure.[4] There were changes to metropolitan area definitions during the decade and thus the geographic references of the mid-decade economic measures did not all correspond to those for the sociodemographic data from the 1990 Census. Moreover, there were some disclosure problems for a few economic variables. Appendix C describes how we dealt with these and other measurement issues.

5. ESTIMATION RESULTS

We estimated models to explain the legal immigrant settlement patterns for the top 10 countries of origin of employment-based immigrants—Canada, China, El Salvador, India, Japan, Korea, Mexico, Philippines, Taiwan, and the United Kingdom. These 10 countries supplied approximately 38,000 of the 85,000 employment-based immigrants to the United States in 1995. Results for place characteristics only are shown in Table 1. The coefficient estimates shown have no direct economic interpretation, except for their sign and statistical significance. As expected, nearly all immigrants appear to be attracted to large metro areas with pleasant climates, educated residents, and high-paying jobs. There are two exceptions. Filipinos and Salvadorans on average are not choosing places where the existing population is highly educated, and Salvadorans are choosing places with poor climates. The enclave effect appears to be important to all groups except those from India and El Salvador. One might expect the presence of large enclaves of coethnics to be unimportant to English-speaking immigrants, like Indians, but our initial results show a positive enclave effect for British and Canadian immigrants. We explore these apparent contradictions in the next set of models. Another interesting result from the simple models is that, contrary to the findings of Jaeger (2000), employment-based immigrants appear not to be attracted by the presence of large immigrant populations (other than that of their coethnics). In

[4]We also estimated models using two other variables suggested in the literature. We constructed a measure of state welfare generosity and a college town index to see if these were important place attractors. Neither variable was statistically significant, perhaps because we have restricted the analysis to employment-based immigrants.

TABLE 1: Effects of MSA Characteristics on the 1995 Location Choices of Legal Immigrants Entering the United States via Employment

	British		Canadians		Chinese		Filipinos		Indians	
Variable	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Enclave	8.8889	6.337	6.1002	14.877	0.1790	1.357	0.4975	4.447	−4.4259	−9.577
Diversity	−0.1849	−14.779	−0.1890	−19.716	−0.0620	−7.467	−0.1525	−18.257	−0.1380	−18.615
Urbanization	0.5167	11.643	0.6104	20.659	0.5729	29.093	0.7628	39.363	0.8077	34.615
College	4.7275	10.483	2.9443	7.575	7.5154	25.046	−0.7615	−1.983	6.0593	19.414
Climate	0.1545	13.696	0.1137	13.053	0.0866	12.788	0.2848	32.477	0.0627	8.825
Average Annual Earnings per Job	0.6774	9.587	0.3883	5.770	1.0321	20.565	1.3177	24.283	1.5167	28.856
Job Growth, Goods Industries	−1.1175	−2.885	−0.1587	−0.499	−0.8392	−2.820	−1.8414	−5.806	−0.3810	−1.316
Job Growth, Service Industries	2.6467	6.134	3.2957	9.105	−1.3568	−3.713	0.7163	2.191	1.6365	4.696
SUMMARY STATISTICS										
n	2448		2803		9515		6761		5076	
L^* (0)	−5636.7283		−6454.1460		−21909.0972		−15567.7778		−11687.9219	
L^* (β)	−3623.4234		−4922.7422		−7711.2418		−6612.5080		−6968.9090	
ρ^2	0.3572		0.2373		0.6480		0.5752		0.4038	

TABLE 1: Continued

	Japanese		Koreans		Mexicans		Salvadorans		Taiwanese	
Variable	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Enclave	17.3630	11.605	5.7726	11.382	0.1218	2.884	−22.8849	−3.839	14.2044	12.585
Diversity	−0.3183	−13.004	−0.3111	−15.048	−0.1606	−6.538	−0.8694	−7.392	−0.3315	−13.900
Urbanization	0.7254	13.961	0.6870	18.920	0.7079	13.151	0.9969	13.474	0.7485	17.840
College	5.3515	6.058	5.5667	8.899	5.4531	6.509	−4.0491	−6.478	6.8735	10.066
Climate	0.1269	6.171	0.2374	17.036	0.3516	16.260	−0.4549	−29.919	0.1863	12.290
Average Annual Earnings per Job	1.1533	9.052	0.7941	8.108	0.7256	4.973	0.4775	4.452	0.9121	9.825
Job Growth, Goods Industries	−0.4441	−0.542	−2.0101	−3.733	1.0285	1.434	−4.3676	−7.986	−1.2823	−2.114
Job Growth, Service Industries	−0.4197	−0.438	−0.4886	−0.852	−2.8829	−3.556	−2.5884	−3.698	−1.0213	−1.427
SUMMARY STATISTICS										
n	1061		2685		1116		1707		1993	
L^* (0)	−2443.0428		−6182.4410		−2569.6850		−3930.5128		−4589.0521	
L^* (β)	−1002.9045		−2318.4519		−1105.7439		−2625.9602		−1799.9606	
ρ^2	0.5895		0.6250		0.5697		0.3319		0.6078	

our results, the coefficient for Diversity is taking a negative sign for all groups but Filipinos, suggesting that cultural diversity so measured is not a positive factor for employment-based immigrants. The effect of recent fast job growth by metropolitan area seems to be mixed across immigrant groups. Fast growth in service sector jobs appears to attract the British, Canadians, Filipinos, and Indians, but has the opposite impact on the Chinese, Mexicans, and Salvadorans. Fast job growth in goods-producing industries is negatively related to immigrant settlement for all groups except those from Mexico[5].

The results just discussed treat immigrants from each country in a uniform way. However, we expect that the place characteristics of metro areas will exert a different attraction according to the gender, age, marital status, and occupational category of the immigrants. To explore this, we estimated models for each immigrant nationality, interacting individual characteristics with destination characteristics. The results are presented in Table 2, where only coefficients that are statistically significant are displayed. These models contain results for variables significant at 0.10, with nearly all variables significant at 0.05. It is clear that immigrants from each country settle differently depending upon their individual characteristics. Consider, for example, the results for Chinese immigrants and the attraction exerted by a large existing Chinese community (Enclave). The first set of coefficient estimates for interaction terms among Chinese immigrants in Table 2 indicate that the Chinese sociodemographic coefficients all impact the effect of the Enclave variable. Males are more influenced by the enclave effect. However, this effect is different for young males and older males, with younger males less attracted to the enclave. Also, if the males are young, single, and professional, the cumulative effect is actually negative, implying that such people do not need to reside in areas containing their ethnic group. This is a much richer result than that shown in Table 1, where the enclave effect for all Chinese—treated homogeneously—was not statistically significant.

As far as we know this is the most complete attempt to simultaneously estimate the effects of individual and place characteristics on immigrant settlement patterns. Clearly, for every immigrant group, there are significant interactions between some of the sociodemographic features of the immigrant and some of the features of the metropolitan areas. Ignoring the interactions can lead to invalid conclusions about the importance of certain place characteristics in attracting immigrants. In many cases, taking account of individual characteristics provides a range for the magnitude of the pull effect of a place characteristic. For example, larger cities with more-educated residents on average attract more British immigrants than smaller cities with less- educated residents, but both effects are even stronger for younger British immigrants.

[5]We checked for multicollinearity among the place characteristics. In so doing, we found collinearity among our measures of Enclave, Diversity, and Urbanization, with the greatest being between Enclave and Diversity. We experimented with removing the collinear variables from the models and found that the parameter estimates and *t*-statistics of the remaining variables were not materially affected. More importantly, the collinearity did not affect the interpretation of results. For these reasons, all place variables were included in the models presented in this paper.

TABLE 2: Effects of MSA and Sociodemographic Characteristics on the 1995 Location Choices of Legal Immigrants Entering the United States via Employment

	British		Canadians		Chinese		Filipinos		Indians	
Variable	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Enclave	8.8488	6.288	6.1033	14.952	1.7406	4.927	1.4593	9.428		
Enclave × Male					0.6824	5.213				
Enclave × Age					−0.6371	−3.673			−3.9063	−7.144
Enclave × Married					−1.2659	−3.987				
Enclave × Professional					−2.1295	−7.353	−2.1438	−9.747	−1.8518	−2.685
Diversity	−0.1381	−7.469	−0.1807	−16.646	−0.0918	−6.756	−0.1840	−14.880	−0.1250	−11.951
Diversity × Male										
Diversity × Age							−0.0311	−3.207		
Diversity × Married	−0.0739	−3.765			0.0262	2.073				
Diversity × Professional			−0.1901	−2.085	0.0310	2.918	0.1265	10.791	−0.0231	−1.731
Urbanization	0.3768	6.005	0.6138	20.813	0.5771	29.096	0.7547	38.424	0.8303	20.084
Urbanization × Male										
Urbanization × Age	0.0820	3.111								
Urbanization × Married	0.1389	2.489							−0.0819	−3.053
Urbanization × Professional									0.0835	1.926
College	2.5048	3.020	2.8930	7.483	8.5283	15.611	6.7814	6.736	6.0423	19.644

College × Male	1.9991	2.480								
College × Age	1.9520	2.369			−1.0225	−1.648	−5.2492	−5.793		
College × Married							−2.7293	−4.125		
College × Professional							−3.2694	−5.118		
Climate	0.1552	13.717	0.1605	10.465	0.1325	6.187	0.3376	13.596	0.1276	6.381
Climate × Male										
Climate × Age					−0.0341	−2.306	−0.0589	−3.025	−0.0723	−3.460
Climate × Married			−0.0661	−3.765	−0.0490	−2.756	0.0486	3.089		
Climate × Professional					0.0795	5.642	−0.0725	−4.643		
Average Annual Earnings per Job	0.6823	9.601	0.4005	6.136	0.9455	16.102	1.1802	11.273	0.8233	7.183
Average Annual Earnings per Job × Male										
Average Annual Earnings per Job × Age							0.2180	1.936	0.8047	6.391
Average Annual Earnings per Job × Married										
Average Annual Earnings per Job × Professional					0.1924	2.124				
Job Growth, Goods Industries	−1.1004	−2.835			−3.4507	−4.555	−1.2064	−2.448		
Job Growth, Goods Industries × Male										

TABLE 2: Continued

	British		Canadians		Chinese		Filipinos		Indians	
Variable	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Job Growth, Goods Industries × Age					1.0307	2.102				
Job Growth, Goods Industries × Married					1.6459	2.698				
Job Growth, Goods Industries × Professional					0.5128	2.200	−1.1415	−1.871		
Job Growth, Service Industries	2.6222	6.068	1.8082	3.415	−1.4222	−3.908	−1.1060	−2.115		
Job Growth, Service Industries × Male										
Job Growth, Service Industries × Age									1.6465	5.270
Job Growth, Service Industries × Married			2.0504	3.415						
Job Growth, Service Industries × Professional							3.6079	5.415		
SUMMARY STATISTICS										
n	2448		2803		9515		6761		5076	
L^* (0)	−5636.7283		−6454.1460		−21909.0972		−15567.7778		−11687.9219	
L^* (β)	−3602.7820		−4905.6037		−7601.2207		−6429.9769		−6935.0738	
ρ^2	0.3608		0.2395		0.65306		0.5870		0.4067	

	Japanese		Koreans		Mexicans		Salvadorans		Taiwanese	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Enclave	17.8420	12.785	5.4464	10.589	0.4403	3.034	−22.8998	−3.818	14.0727	12.349
Enclave × Male			0.6730	2.695						
Enclave × Age					−0.3932	−2.765				
Enclave × Married										
Enclave × Professional										
Diversity	−0.3206	−13.153	−0.3098	−14.973	−0.1299	−3.967	−0.9056	−7.491	−0.3030	−11.566
Diversity × Male					−0.0489	−1.751				
Diversity × Age									−0.0388	−2.789
Diversity × Married										
Diversity × Professional										
Urbanization	0.7230	13.946	0.6853	18.847	0.7499	13.173	1.0382	13.716	0.8406	15.606
Urbanization × Male										
Urbanization × Age										
Urbanization × Married									−0.1105	−2.763
Urbanization × Professional							−0.4850	−2.166		
College	5.1799	5.996	5.6107	8.995	7.3980	7.811	−4.0542	−6.413	6.8444	10.024
College × Male										
College × Age										
College × Married										
College × Professional					−6.6607	−4.008				

TABLE 2: Continued

	Japanese		Koreans		Mexicans		Salvadorans		Taiwanese	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Climate	0.1826	5.258	0.2373	17.018	0.4586	16.131	−0.4712	−29.607	0.3961	8.664
Climate × Male										
Climate × Age									−0.1073	−3.082
Climate × Married	−0.0797	−2.116							−0.1590	−4.584
Climate × Professional					−0.3165	−7.728	0.3273	5.672		
Average Annual Earnings per Job	1.2136	10.958	1.0050	8.140			0.4859	4.487	0.9348	10.070
Average Annual Earnings per Job × Male										
Average Annual Earnings per Job × Age			−0.3367	−2.880	0.7227	4.856				
Average Annual Earnings per Job × Married										
Average Annual Earnings per Job × Professional										
Job Growth, Goods Industries			−3.049	−5.351	3.2354	2.613	−1.5550	−1.717	−1.6950	−3.300
Job Growth, Goods Industries × Male										
Job Growth, Goods Industries × Age					−2.4627	−1.803	−3.3932	−3.685		

Job Growth, Goods Industries × Married							
Job Growth, Goods Industries × Professional		3.3409	3.705				
Job Growth, Service Industries				−4.2019	−4.470	3.4015	3.451
Job Growth, Service Industries × Male						−5.2002	−5.204
Job Growth, Service Industries × Age							
Job Growth, Service Industries × Married						−6.6712	−6.648
Job Growth, Service Industries × Professional		−2.3431	−2.448	4.4317	3.260		
SUMMARY STATISTICS							
n	1061	2685		1116	1707		1993
L^* (0)	−2443.0428	−6182.4410		−2569.6850	−3930.5128		−4589.3052
L^* (β)	−1001.1030	−2304.1292		−1049.6147	−2566.7273		−1777.0455
ρ^2	0.5902	0.6273		0.59154	0.3470		0.6128

It is particularly interesting to observe results where the sign of the estimated coefficient changes on a place characteristic variable when one considers the variation in individual characteristics. For example, working in a professional occupation more than offsets the enclave attraction for Filipinos and the Chinese, regardless of gender, age, or marital status. Salvadorans are not attracted to places with fast growth in service sector jobs if they are male and/or married. Japanese appear to be the nationality with the least significant interaction effects. Immigrants from Japan behaved uniformly across sociodemographic characteristics, except that married Japanese are pulled less toward places with better climates.

Surprisingly, the significant enclave effect for British and Canadian immigrants observed in Table 1 holds up even when accounting for interactions with their personal characteristics. One does not expect employment-based immigrants from affluent English-speaking countries to need the economic security provided by proximity to others from their home country. Yet our more elaborate models show a highly significant enclave coefficient for both groups and across all the sociodemographic variables. For these two groups, the apparent anomaly may be due to our measure of enclave. We use the number of foreign-born of the same nationality living in a metro area as a measure of the size of the enclave, whether or not the persons live physically close to one another. In other words, many Canadians may choose to live well-dispersed in a U.S. city and for reasons other than the joint economic security typically ascribed to enclaves. Izyumov et al. (2002), show that the majority of new immigrants to the United States live in a small number of postal zip codes of the major gateway cities. However, of the 17 immigrant groups studied, the British and Canadians were the least concentrated. Thus, at least in the case of these two groups, our enclave measure is picking up some other effect, perhaps the historical tendency of the British and Canadians to continue choosing the same metros as a destination because of professional opportunities not available in their home markets.

6. CONCLUSIONS

We have specified and estimated multinomial logit models of location choice for legal employment-based immigrants from the top 10 countries of origin. We defined the choice set to be 298 metropolitan areas in the United States, and developed eight measures to characterize the economic attractiveness of each place. We acquired INS data on the intended postal zip code of residence for each immigrant, as well as sociodemographic information on each person, and these were further coded by metropolitan area. When we did not take account of possible interactions between the characteristics of the individuals and the characteristics of the places, our results were roughly consistent with what others have found. Employment-based immigrants are generally attracted to large cities with a nice climate, high wages, and educated population (see Buckley, 1996; Zavodny, 1998; Dodson, 2001). However,

in contrast to Jaeger (2000), we found employment-based immigrants not attracted to cities with an ethnically diverse population.

Most importantly, there appears to be great variation in the importance of place attractors for immigrants when one considers their age, gender, marital status, and profession. Metropolitan place characteristics that seem to attract one group of immigrants from a certain country may have the opposite impact on a different group from the same country. We found, for example, that while Chinese employment-based immigrants as a group are sensitive to the enclave effect, the younger and more educated among them are not. Important interactions between individual and place characteristics were found to be most pervasive for the Chinese and Filipinos and least so for Canadians and the Japanese. Overall age and marital status appear to be the most important factors differentiating location decisions of immigrants of the same national and professional group.

This is a richer result than previously reported in the literature. The direction of research represented by our results, if expanded, could play a role in immigrant-related policy planning, for hypothesis testing, policy analysis, or forecasting. As noted by other investigators (see, for example, Jaeger, 2000) settlement patterns of immigrants in the United States depend significantly upon the admission criteria, which determine some of the key individual characteristics of immigrants, such as their country of origin and level of education. Being able to predict location patterns of immigrants based on these characteristics can be a helpful tool for policymakers at the federal and local level.

Thus federal authorities, interested in a more equal distribution of employment-based immigrants across the nation, can use comprehensive location choice models to better evaluate the impact of planned changes in immigrant admission quotas. For example, our finding that Indian, Chinese, and Filipino immigrants are not sensitive to the enclave effect indicates that, other things being equal, increasing the number of professional immigrants from these groups would lead to a more dispersed immigrant settlement pattern. Similar patterns will probably be true for the approximately 1.3 million foreign students and H-1B professionals who represent one of the main sources of employment-based immigration to the United States.[6]

At the same time, local and state governments can use immigrant location choice models to better structure the incentives aimed at attracting higher-skilled "value-increasing" immigrants to their regions.[7] These regions

[6]As of 2002, the United States had a total of 583,000 foreign students and 710,000 H-1B professionals (*Economist*, August 23, 2003, p. 21; *The Wall Street Journal*, October 27, 2003, p. A13).

[7]In the past 10 years, several states and cities in the United States tried to emulate the success stories of immigrant-fuelled economic growth, such as in California's Silicon Valley, by developing regional immigrant-attraction programs. In the course of the 1990s such efforts were undertaken in Iowa, as well as in Pittsburg, Pennsylvania, Nashville, Tennessee, and Louisville, Kentucky. Regional immigration policies have long been in use in Canada, where seven out of ten provinces have special agreements with the Federal government giving them additional powers in attraction and settling of immigrants (Buckley, 1996).

generally have very small foreign-born communities, making them unattractive to most new immigrants. However, knowing which categories of potential immigrants are less sensitive to enclave effects would allow such regions to develop more pointed immigrant attraction programs by focusing on groups that are more mobile and need less of an incentive to come to places having few or none of their compatriots.

More generally, development of a comprehensive model of immigrant settlement, which simultaneously evaluates both the characteristics of immigrants and their potential destinations, provides an intellectual basis for an integrated immigration policy. Such policy would combine refinement of existing immigrant admission policy with the development of specific, and now practically nonexistent, measures focused on settlement and assimilation of immigrants *after* they are already in the country. (For a useful discussion of "immigration" versus "immigrant" policy see Fix, Zimmerman, and Passel, 2001.)

Further research should help develop interactive location choice models that take into account large numbers of individual characteristics of locations and attributes of immigrants. To increase their analytical and predictive strength, existing models may be further disaggregated and enhanced with additional information, such as the data now available from the 2000 Census. Also, as computational problems are solved, we would like to develop a model that is less static. A cohort-component technique could be devised to update decennial estimates of the stock of foreign-born persons with annual INS data on immigration. Then we could explore the effect of changing economic conditions on immigrant location choice among metropolitan areas. We could also better model the timing of actual arrival of employment-based immigrants versus the date of legal residence. Moreover, we need to further develop our models so as to better understand the pull exerted by large existing populations of the foreign-born. The models presented here, while more disaggregated than any to date, still need refinement to satisfactorily explain location choices for all important immigrant groups.

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APPENDIX A

TABLE A1: Comparison of Multinomial Logit Model Coefficients Obtained from Two Approaches to Choice Set Generation

	Indians		Taiwanese	
Variable	Model 1[a]	Model 2[b]	Model 1	Model 2
Enclave	−5.4563	−5.3776	13.4951	13.1533
Diversity	−0.1248	−0.1364	−0.2900	−0.3300
Urbanization	0.7550	0.7987	0.6604	0.7490
College	6.0785	5.9381	6.8332	6.9013
Climate	0.0608	0.0642	0.1910	0.1867
Average Annual Earnings per Job	1.5782	1.5444	0.8062	0.9197
Job Growth	1.0500	1.0470	−2.1620	−2.2407
n	5076	5076	1993	1993

[a]Estimated using 298 MSAs as location alternatives.

[b]Estimated using 10 MSAs as location alternatives (i.e., 9 MSAs were drawn randomly from the universal choice set and added to the chosen alternative).

APPENDIX B

TABLE B1: Sociodemographic Characteristics of Legal Immigrants Entering the United States via Employment in 1995[a]

	Sociodemographic Characteristics				
Nationality	Female (%)	Married (%)	Professional (%)	Mean Age	Number
British	46	69	57	37	2,448
Canadians	53	69	56	35	2,803
Chinese	46	78	21	35	9,515
Filipinos	59	67	57	33	6,761
Indians	46	85	57	31	5,076
Japanese	48	67	42	37	1,061
Koreans	51	74	32	36	2,685
Mexicans	46	67	19	31	1,116
Salvadorans	52	57	3	31	1,707
Taiwanese	52	73	49	34	1,993

[a]Computed for immigrants aged 16 to 64 years.

APPENDIX C

DATA AND MEASUREMENT ISSUES

This study uses 1990 Census data on the foreign-born population in metropolitan areas; annual data compilations of the U.S. Immigration and Naturalization Service, titled "Immigrant Public Use Tapes" for fiscal years 1990 through 1998; and metro-level annual economic data from the U.S. Bureau of Economic Analysis. In combining data from these sources, we had to address a number of measurement issues.

The 1990 Census PUMS 1% file provides individual records, including detailed socioeconomic data, on a 1 percent sample of respondents to the long survey. Importantly, the data set provides each resident's place of birth, wherever in the world. The coverage of the Census differs from the INS data on legal immigrants, in that the Census measures the stock of immigrants and ostensibly counts everyone, including temporary foreign-born residents—students and visitors—and illegal residents. We use 1990 Census snapshots of the foreign-born population in each metro area as an indicator of the "enclave strength" for each nationality. As the number of foreign-born persons change in each metro throughout the decade, due to new migrants, deaths, and secondary migration, the 1990 Census estimates become less representative. However, since there are no detailed intercensal estimates of the foreign-born stock by nationality for all metro areas, the Census provides the best measure available for studies such as ours. Greenwood, McDowell, and Trabka (1991) discuss the factors affecting census counts of foreign-born persons, as well as a cohort-component method of estimating net migration to metropolitan areas between decennial censuses.

The INS compilations contain individual records on each alien legally admitted for permanent residence during each fiscal year. The records include data on age, gender, countries of birth and last residence, port of entry, class of admission (refugee, family and employment), declared occupation, and zip code of intended residence. Importantly, they do not include data on education levels or family status (naturalizing with spouse or children). We acquired data for nine fiscal years, for a total of around eight million records. For this study, we selected only those records pertaining to persons aged 16 to 64 immigrating under an employment-based status. We used records for only 1995 for the ultimate multinomial logit model, but used data for all years to construct immigrant flow populations for Figure 3. Employment-based immigrants accounted for about 10 percent of the nine million total during the 1990–1998 period. Greenwood and McDowell (1999) discuss characteristics of the INS data. Newbold (2000) compares census and INS data sets to see whether the "intended" residence as coded in the INS data set is representative of actual settlement patterns, given the tendency of immigrants to move once admitted. Comparing the patterns evident in the INS data to those in the 1985–1990 cohort of immigrants measured in the 1990 Census, he found evidence of secondary (and return) migration, but no evidence of overall dispersion or concentration among metropolitan areas or states. In other words, the INS data seem to represent ultimate immigrant distribution patterns relatively well.

Admission Class

The immigrants during the study period fell under 234 INS classes of admission codes, and we have organized these into four major categories: family-based immigration, including immediate relatives of U.S. citizens; employment-based immigration; refugees and asylees; and other immigrants. Separate queries were made to our database for each year to aggregate immigrants by these categories. The published documentation does not provide enough information to aggregate the detailed class of admission codes into categories. We were able to classify 168 of these codes using INS *Statistical Yearbook* tables. The Department of Policy and Planning at the INS helped us in classifying the remaining 66 codes, though they evidently do not have a single document that has all of the class of admission codes that have been used in this and other time periods. We did not differentiate between primary and beneficiary employment-based immigrants. Existing studies (Jaeger, 2000) indicate that their settlement patterns do not differ significantly.

Time in United States

The INS data record the date of immigrant settlement in the United States based on the timing of approval of their permanent residency application. However, many immigrants live in the United States for years under

temporary visas (e.g., students, H-1B professionals) or illegally. Due to backlogs at the INS, the lag between actual arrival of these persons to the United States and adjustment of their status to that of a permanent resident ("green card" holder) can be as short as one year or as long as ten years. For a more detailed discussion, see Jaeger (2000), who found that on net the geographic distribution of immigrants remains unchanged five years after declaring their "intended residence."

Geography

We acquired data from three sources—the 1990 Census, the Immigration and Naturalization Service (INS), and the U.S. Bureau of Economic Analysis (BEA). The Census and BEA data are geocoded for metropolitan areas, though there are some differences in metro definitions between the two sets. The INS data are geocoded for the "zip code of intended residence" of new immigrants. We aggregated the zip code data to metropolitan areas.

We chose to treat primary metropolitan statistical areas (PMSAs) as separate places rather than simply include them as part of their larger consolidated metropolitan statistical areas (CMSAs). The PMSAs are large MSAs that have grown to be contiguous over time and are now defined to form CMSAs—each containing two or more PMSAs. As of the end of the decade, there were 17 CMSAs defined, containing a total of 58 PMSAs. Using PMSAs rather than CMSAs is somewhat arbitrary as, for example, residents of the Gary, Indiana, PMSA certainly identify themselves as part of the greater Chicago CMSA market. However, it is also true that PMSAs each have their own distinct urban cores, demographies, histories, and industrial structures, and we want to allow the possibility of distinct immigrant pull factors in our analysis. The Dallas and Fort Worth PMSAs are clearly different, even though the combined area (CMSA) shares a major airport and freeway system, and workers from both sides fill jobs in the booming area between the two cities. We decided to use PMSAs because of the great variety in economic conditions and demographic structures among the components of the largest CMSAs. The New York CMSA, for example, includes such diverse and physically distant places as New Haven, Connecticut; Manhattan; the Bronx; Newark and Trenton, New Jersey; and Long Island. The San Francisco CMSA includes the metropolitan areas of Oakland, San Jose, and Santa Cruz. While it seems plausible to consider the smaller Cincinnati, Denver, Portland, and Sacramento CMSAs as coherent destination choices, we do not believe that in general CMSAs represent as full a range of place attractors as do PMSAs. This is ultimately an empirical question, though, one we have not yet addressed. See the U.S. Bureau of the Census (1991, 1998) for listings of MSA component counties as of the 1990 Census and the subsequent years, respectively.

Our analysis included observations on 298 MSA or PMSA destinations. This is fewer than the 328 metropolitan areas defined as of the late 1990s, the

difference due to changing metro definitions and some compatibility problems for New England metros. Our statistical work required that we merge the 1990 Census data with the immigration and economic data for the subsequent decade. There were 334 MSAs and PMSAs as of the 1990 Census. Some of these were combined after the Census. For example, the Midland MSA and Odessa MSA were combined to create the Midland-Odessa, Texas, MSA. In all, there were 17 mergers affecting 39 pre-Census MSAs. We aggregated the Census data accordingly to reflect the mergers.

Moreover, MSAs and PMSAs in New England are defined along town and city boundaries, not county boundaries as is conventional in the rest of the United States. The PUMS-based 1990 Census data on foreign-born residents uses these metro definitions. The BEA economic data for New England metros are based on county boundaries, and are called New England County Metropolitan Areas (NECMAs). Because of this incompatibility we have omitted observations for the eleven NECMAs: Bangor, Maine; Barnstable, Massachusetts; Boston, Massachusetts; Burlington, Vermont; Hartford, Connecticut; Lewiston, Maine; New London, Connecticut; Pittsfield, Massachusetts; Portland, Maine; Providence, Rhode Island; and Springfield, Massachusetts.

Also, there are 19 metropolitan areas that have been created since the 1990 Census was taken: Auburn-Opelike, Alabama; Barnstable-Yarmouth, Massachusetts; Corvalis, Oregon; Dover, Delaware; Flagstaff, Arizona-Utah; Goldsboro, North Carolina; Grand Junction, Colorado; Greenville, North Carolina; Hattiesburg, Mississippi; Jonesboro, Arkansas; Missoula, Montana; Myrtle Beach, South Carolina; Newburgh, New York-Pennsylvania; Pocatello, Idaho; Punta Gorda, Florida; Rocky Mount, North Carolina; San Luis Obispo-Atascadero-Paso Robles, California; Sumter, South Carolina; and Yolo, California. We dropped these from our sample, as 1990 PUMS data on foreign-born residents by nationality was not available. Researchers should be alert that the names and codes were changed on two MSAs after the 1990 Census, though they continued to represent the same geographic area. The Anaheim-Santa Ana, California, PMSA became the Orange County, California, PMSA, and the Oxnard-Ventura, California, PMSA became the Ventura, California, PMSA. Moreover, a completely new set of metropolitan and micropolitan area definitions were announced by the Office of Management and Budget in June 2003. These will need to be incorporated for analyses of location subsequent to the 2000 Census.

Since we are interested in the distribution of new legal immigrants, by type, among U.S. metropolitan areas, we had to map the zip code-based INS data to MSAs and PMSAs. This turned out to not be a trivial exercise, even given the powerful GIS tools now available. First, zip codes are defined by the U.S. Postal Service and are modified as needed for administrative purposes. They do not necessarily conform to county outlines and they change over time. Second, as discussed above, MSA definitions have changed somewhat during the decade.

To address the first problem, we obtained a zip code to MSA mapping file from the Geography Division of the U.S. Census Bureau. This contained over

40,000 unique zip codes. Out of these, 523 zips belonged to multiple PMSAs and 1,941 zips came under both a MSA and a nonmetro area. In the case of zips that came under multiple PMSAs, we classified the zips under the PMSA having the largest population. In cases where a zip came under both a MSA or PMSA and a nonmetro area, they were classified under the metro designation.

Confidentiality

BEA's estimates of jobs by industry are subject to federal disclosure restrictions when publishing an industrial total would effectively reveal the employment count of an individual firm. While our job growth calculations were performed at a quite aggregated industrial level, this disclosure restriction affected around a dozen metropolitan areas. In those cases, we filled in nondisclosed data by either interpolating between the closest two disclosed data points, or by extrapolating from the last disclosed data point using the compound annual growth rate over the previous five years. Also, in some cases BEA provides estimates of jobs by industry in a year when all the underlying data have not been received from firms, though the estimate published "constitutes the major portion of the true estimate." In those cases, we simply accepted the published estimates.