Discovering Diverse Mechanisms of Migration: The Mexico–US Stream 1970–2000

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Scholars have identified diverse mechanisms that lead individuals to migrate. These mechanisms are analyzed in various migration theories developed in multiple disciplines. In neoclassical economics, higher wages in the destination country propel the migration of individuals who expect to earn more there. In the new economics of migration, the uncertainty in the origin economy leads to migration by households or household members who face risks to domestic earnings. In cumulative causation theory, the growing web of social ties between countries of origin and destination fosters the migration of individuals who are connected to earlier migrants.

In a series of seminal publications, Massey et al. (1993, 1994, 1998) argued that the various causal configurations implied by different theories are not mutually exclusive. Income-maximizing migrants can co-exist alongside migrants who seek to diversify risks or alongside those who join family or friends at the destination. Massey and Espinosa (1997) provided the first empirical application of this argument in the Mexico–United States setting. Associating each theory with a set of independent variables, the authors used regression analysis to compare which variables and theories best predict who migrates. This empirical approach, although commendable in combining various theories, did not fully reflect Massey et al.'s (1993) conceptualization, since it treated theories as competing rather than complementary accounts of migration. The approach also did not consider the conditional nature of theories, that is, the fact that each theory applies to a specific group of individuals under specific conditions.

In more recent work, Massey and Taylor (2004: 383) critiqued their earlier approach (Massey et al. 1998) for not being able to "state with any precision which theories were most important empirically in accounting for variations in the number, rate, and characteristics of immigrants over time and whether and why different theories may prove more or less efficacious in accounting for immigration patterns in different times and places," and they identified the major challenge for migration research to be "test[ing] various theoretical explanations comparatively…to determine which ones prevail under what circumstances and why."

The present study addresses the challenge of characterizing the causal heterogeneity of migration. Thus it confronts a major methodological problem in social science: identifying the different mechanisms at work among different groups of individuals. In an effort to emulate the natural sciences (Lieberson and Lynn 2002), quantitative social inquiry often focuses on (and generalizes from) an average case rather than studying the variability across cases (Duncan 1982; Xie 2007). In recent years, however, new methods, such as multi-level, latent class, or growth curve models, have allowed researchers to study the variability in outcomes across different contexts, groups, or trajectories (Raudenbush and Bryk 1986; D'Unger et al. 1998; Muthén and Muthén 2000).

Migration research has closely followed these developments. Studies have used split samples, interaction terms, or hierarchical models to identify the different factors influencing migration for men and women, among different ethnic groups, or in different contexts and time periods (e.g., Kanaiaupuni 2000; Marcelli and Cornelius 2001; Massey, Goldring, and Durand 1994). But each of these studies relied on a few fixed categories, such as gender or community, to characterize the heterogeneity in migration, an approach that can be considered restrictive, even essentialist (Somers 1994).

In this study, rather than dissecting or modeling data based on a few selected attributes, we seek to discover the *configurations* of various attributes that characterize different migrant types. This approach is inspired by Ragin and Abbott's work in sociology. Ragin (1987) argued that multiple causal bundles may lead to the same social or historical outcome, and these bundles may include various conditions that come together. To discover these causal bundles, he developed methods based on Boolean algebra and fuzzy-set theory (Ragin 2000). Abbott (2001) similarly defined causes as specific configurations or sequences of events and applied sequence analysis, a method originally developed for classifying DNA patterns, to social data (Abbott and Hrycak 1990).

Like Ragin and Abbott, we argue that different configurations of causal factors may lead individuals to the same outcome—in the present case, to migrate from Mexico to the United States. To discover these configurations, we employ cluster analysis, an inductive and data-driven method for locating groups of cases with similar attributes. This method allows us to identify distinct types among migrants and thus to characterize variation across cases, rather than focusing on an average case. Hence, instead of asking "What factors determine who migrates?," one can now ask "Are there different types of migrants in different contexts? And are these types identified by different theories?"

Identifying configurations that characterize "ideal" types has a long tradition (Weber [1922] 1978). But, today, this tradition survives mostly in qualitative work. By using cluster analysis to discover different migrant types, we appropriate a quantitative method for a distinctly qualitative approach to social science. We then relate each migrant type to a theoretical narrative and offer an alternative way of linking evidence to theory, where different narratives provide complementary, rather than competing, accounts of migration. Finally, we juxtapose the temporal distribution of each migrant type against the major trends in the economic and political context of Mexico-to-US migration and identify when, under what conditions, and for whom each theory is most relevant, a strategy closely related to the methodology of small-N case studies.

This approach provides novel insights to understand the migration stream between Mexico and the United States, the largest international flow globally in the study period. That period begins in 1970 and exhibits various important changes in the migration context until 2000: economic fluctuations in Mexico leading to increased migration, shifts in US migration policy intended to prevent it, and growing undocumented migration between the two countries. We use data from the Mexican Migration Project from about 17,000 migrants on the year of their first migration to the United States. The analysis, which applies the K-means clustering algorithm with various validation checks, yields four distinct migrant types. Each type displays a distinct configuration of individual, household, and community characteristics and corresponds to a specific theory of migration. Furthermore, each migrant type becomes prevalent in a specific period, depending on the economic, social, and political conditions in the two countries. We also demonstrate that as each migrant type becomes prevalent, a theory corresponding to it is developed.

Background

The origins of migration

Today some 200 million people, roughly 3 percent of the world population, reside in a country other than the one in which they were born (World Bank 2009). With specific reference to the US, Portes and Rumbaut write: "Underneath its apparent uniformity, contemporary immigration features a bewildering variety of origins, return patterns, and modes of adaptation to American society. Never before has the United States received immigrants from so many countries, from such different social and economic backgrounds, and for so many reasons" (Portes and Rumbaut 2006: 13). The increasing mobility of people, mainly for labor, has led to a rapid growth in migration research in the past four decades. This research has sharpened our understanding of the migration process, but it has also led to a fragmented set of theories developed in multiple disciplines (Menjívar 2010).

In neoclassical economics, labor migration is viewed as a product of wage and employment differentials between regions (Harris and Todaro 1970; Sjaastad 1962). Individuals from a low-wage origin seek to maximize their income by migrating to a high-wage destination (Todaro 1969, 1977). The most likely migrants are individuals whose education and/or occupation permit higher earnings at the destination compared to the origin. These predictions have received substantial empirical support. At the aggregate level, for example, researchers related Mexico-to-US migration rates to wage and employment figures in the two countries (Bean et al. 1990; Frisbie 1975; Jenkins 1977; White, Bean, and Espenshade 1990). At the individual level, researchers showed that the expected earnings at the destination strongly influenced whether an individual migrates from Mexico (Massey and Espinosa 1997; Taylor 1987), El Salvador (Funkhouser 1992), and Paraguay (Parrado and Cerrutti 2003).

The new economics perspective views labor migration as a household decision in response to economic uncertainty in developing countries (Stark and Bloom 1985; Stark, Taylor, and Yitzhaki 1986). Given insufficient markets for insurance, households send migrants as a risk-diversifying strategy, where earnings at the destination provide a hedge against shocks to domestic income (Stark 1984; Stark and Levhari 1982). As a result, migrants tend to originate from households with substantial economic resources, a pattern observed in various settings including Mexico (Massey et al. 1987), the Dominican Republic (Grasmuck and Pessar 1991), and the Philippines (Root and De Jong 1991). An alternative formulation of this theory considers credit market failures in developing economies. In that case, households send migrants to overcome capital constraints and to decrease their relative deprivation in the origin community (Stark and Taylor 1989, 1991; Stark and Yitzhaki 1988). This formulation is the culmination of earlier findings from case studies that established migration as a strategy for supporting local farms or businesses (Cornelius 1978; Wiest 1973), as well as recent results which showed that migrants' earnings are often invested in the origin community (Durand, Parrado, and Massey 1996; Lindstrom and Lauster 2001; Massey and Parrado 1994).

Both the neoclassical and the new economics perspectives focus on the economic conditions that initiate labor migration. Cumulative causation theory shifts this focus to the social structure that sustains it (Massey 1990a, 1990b). In this theory, past migration develops a growing web of social ties between origin and destination regions. These ties increase the likelihood of future movement by lowering the costs and increasing the benefits of migrating (Massey and García-España 1987). The most likely migrants are individuals who have family or community ties to earlier migrants at the destination.

Strong evidence confirms this expectation in Mexico (Davis and Winters 2001; Massey and Espinosa 1997; Massey and Zenteno 1999; Winters, De Janvry, and Sadoulet 2001) and Thailand (Curran et al. 2005; Garip 2008).[1]

Two other theories make predictions about aggregate migration flows, but not about the *specific characteristics* of migrants, hence are not elaborated in this study. Segmented labor markets theory attributes migration to the labor demand inherent in industrialized economies (Piore 1979). Migrants fill the unskilled jobs that are undesirable to native workers because of their low wages and status. In world systems theory, migration stems from the expansion of capitalist economies into developing countries (Wallerstein 1974). Migrants seek livelihoods abroad in response to the economic disruptions in their own countries and by capitalizing on their increasing cultural connections to developed regions resulting from globalization (Castells 1989; Sassen 1988, 1991).

A gap between theory and evidence

Here we focus on three theories that predict different types of migrants mobilized for different reasons. Neoclassical economics anticipates income-maximizing migrants who expect to earn higher wages at the destination. New economics predicts risk-diversifying migrants who seek to complement earnings that are at risk in the place of origin. Cumulative causation describes network migrants who follow family or friends at the destination. Each theory depicts a unique facet of the migration process and, together, they provide a more complete picture. The work of Massey et al. (1993, 1994, 1998), mentioned earlier, was an impressive effort to integrate various theories of international migration. These theories, the authors argued, carry distinct implications that need to be integrated in a common analytic framework and evaluated empirically.

Massey and Espinosa (1997), in their comprehensive analysis of the Mexico–US case, provided the first empirical application. They identified variables that captured the predictions of various theories. The inflation rate in Mexico, for example, measured the level of economic uncertainty, a catalyst for migration in new economics theory. The prevalence of migration in the origin community signified the density of connections to earlier migrants, an important factor leading to migration according to cumulative causation theory.

Using a regression model and 41 variables, Massey and Espinosa determined which variables best predict who migrates from 25 Mexican communities over 25 years. The variables corresponding to the new economics and cumulative causation theories obtained substantively meaningful and statistically significant coefficients. These theories, the authors argued, received strong empirical support. The variables capturing neoclassical, segmented markets, and world systems perspectives had less conclusive coefficients leading to weak support for those theories. This empirical approach, based on regression analysis, exhibits a gap between theory and evidence on migration. First, the approach juxtaposes theories against one another as competing explanations of migration. Second, the approach produces average results that are presumed to generalize to all individuals and across time. The results imply that migration theories, conditional statements in reality, apply universally.

More recently, migration scholars have addressed the issue of population heterogeneity, that is, the fact that different mechanisms may work for specific groups of cases. Scholars, for example, have shown the different reasons underlying the migration of men and women (Cerrutti and Massey 2001; Curran and Rivero-Fuentes 2003; Donato 1993; Hagan 1998; Hondagneu-Sotelo 1994; Kanaiaupuni 2000; Pessar 1999). Students of assimilation have demonstrated different patterns of integration into the host society among migrants from different ethnic groups (Alba and Nee 1997; Portes and Rumbaut 2006; Portes and Zhou 1993). Others have studied the varying causes of migration over time or across communities (Durand, Massey, and Zenteno 2001; Fussell and Massey 2004; Lindstrom and Lauster 2001; Marcelli and Cornelius 2001; Massey et al. 1994).

The present study builds on these efforts and proposes a novel approach to characterize the causal heterogeneity in migration. Rather than dissecting data based on a few selected attributes, this approach employs cluster analysis to discover the distinct causal factors that characterize different migrant types.

Migration from Mexico to the United States

Major milestones since 1942

We focus on migration from Mexico to the United States between 1970 and 2000. This flow gained steam with the Bracero program, which recruited 4.6 million Mexican workers to the United States for short-term farm labor from 1942 through 1964 (Cornelius 1978). The termination of the Bracero program marked a shift in US immigration policy. Changes to the Immigration and Nationality Act in 1965 and 1976 severely limited the number of visas available to Mexicans. This condition, combined with the economic downturn in Mexico brought on by peso devaluations in 1976 and 1982, sparked an influx of undocumented migrants to the United States. From 1965 to 1986, about 5.7 million Mexican migrants entered the country, 80 percent of them undocumented (Massey, Durand, and Malone 2003).

This period of mostly unhindered undocumented migration ended with the Immigration Reform and Control Act (IRCA) in 1986, which increased border enforcement and imposed sanctions on employers hiring undocumented migrants. The legislation also granted amnesty to 2.3 million undocumented Mexican migrants (US INS 1990). As an unintended consequence, the amnesty created incentives for the relatives of the newly legalized Mexicans to migrate as well (Massey and Espinosa 1997). As a result, undocumented migration to the United States continued through the 1980s, considered the "lost decade" for Mexico's economy (Sheahan 1991).

In 1994, two important events, a peso devaluation in Mexico and the North American Free Trade Agreement (NAFTA) between Mexico, the United States, and Canada, contributed to increasing migration flows to the United States. The devaluation led to the worst economic decline in Mexico in decades, and NAFTA displaced rural farmers through deregulation in agriculture. As a result, from 1994 to 1998, US border apprehensions rose from 1.1 million to 1.7 million (Martin 2003). By 2000, the number of Mexican-born persons in the United States had reached 8.4 million, of whom 3.9 million were estimated to be undocumented (Bean et al. 2001).

Study data

The majority of quantitative results on Mexico-to-US migration are based on data from two surveys: the Mexican National Survey of Population Dynamics (ENADID) and the Mexican Migration Project (MMP).[2] The former is a representative national sample but contains information only on labor migrants. The latter is from specific Mexican communities but covers all migrants, including those who have moved to the United States to join family members. The inclusion of all migrants, not just labor force participants, makes the MMP data more useful for studying the diversity of the Mexico–US stream. These data are not strictly representative of the Mexican population. Yet, prior work found that the MMP data yield an accurate profile of Mexican migrants to the US, and this profile is largely consistent with that observed in the ENADID data (Durand, Massey, and Zenteno 2001; Zenteno and Massey 1998).

The MMP data come from 124 communities located in major migrant-sending areas in 21 Mexican states. Each community was surveyed once between 1987 and 2008, during December and January, when migrants to the US are mostly likely to visit their families in Mexico. In each community, individuals (or informants for absent individuals) from about 200 randomly selected households were asked to provide demographic and economic information and to state the time of their first and their most recent trip to the United States. Household heads were additionally asked to report the trips in-between. These data were supplemented with information from a non-random sample of migrants identified through chain-referral sampling in the United States (about 10 percent of the sample).

Because more detailed information is available for household heads, most studies using the MMP have restricted attention to this sub-population. To provide a more representative portrait of migrants, our study considers all household members. The analysis seeks to identify the diversity in the attributes of migrants on their first trip to the United States. Subsequent trips are not considered because they are recorded only for household heads and because many attributes related to migration behavior are also changed by migration. Over successive trips, migrants gradually gain more experience, establish stronger ties to the destination, and become wealthier. Their attributes change, not as a result of the changing selectivity of the stream, but because of the changes caused by earlier trips. Focusing on first-time migrants allows observation of migrants' attributes independently from this reciprocal relationship.

A concern with the MMP data is the retrospective nature of the information on migrants. Consider a household surveyed in 1990, in which a daughter has migrated to the United States for the first time in 1980. Her attributes, such as age and education, were recorded in 1990, but could be back-projected linearly to 1980. The economic status of her household could be reconstructed using data on the timing of asset purchases. The characteristics of her community could be traced back using the retrospective community history. All of these plausible steps rely on one crucial assumption: that the daughter in question was living in the same household and community in 1980. While this assumption is viable for most cases, the study cannot account for the cases for which it is not.

Methods

Cluster analysis vs. regression analysis

Cluster analysis is a method for discovering groups with similar attributes in data. This method is widely used in fields as diverse as biology, physics, and computer science to produce effective descriptions of typically large and complex data sets. Yet, in the social sciences, the method has been overshadowed by the overwhelming dominance of regression analysis.

Regression analysis estimates parameters that characterize a relationship between an outcome and several attributes. These parameters identify causal effects if the researcher can credibly account for the unobserved heterogeneity in data. The causal effects, if expected to be constant over time, may lead to reliable outcome predictions. Cluster analysis produces a very different output. Rather than search for associations with an outcome, the method discovers groups within the data based on the variability in several attributes. The results, although purely descriptive, may show useful associations to outcomes of interest. For example, different groups of migrants from Mexico may display different settlement and assimilation patterns in the United States.

The two methods also assume different data structures. Regression methods envision a uniform distribution of cases over the attribute space. Yet, in most social data the attributes are correlated and the cases cluster around a few distinct configurations (Abbott 2001; Ragin 1987). Regression methods can take these configurations into account by introducing interactions between attributes. But the number of possible interactions increases exponentially with the number of attributes and quickly renders the model unmanageable. Cluster analysis is a more efficient method for identifying the observed configurations of attributes.

Clustering and regression methods present different approaches to learning from data. The usefulness of either approach depends on the questions of interest, as well as the structure of the data. In this study we seek to discover distinct types of migrants based on various attributes in the MMP data. Qualitative studies suggest the presence of distinct groups among Mexico-to-US migrants (Portes and Rumbaut 2006), and quantitative analysis shows significant interactions among attributes in relation to migration behavior (Curran and Rivero-Fuentes 2003). Both the question of interest and the suspected structure of data point to cluster analysis as the method of choice.[3]

Steps in cluster analysis

Choosing the relevant attributes. The first step in cluster analysis is selecting the attributes for partitioning the data. This process, similar to variable selection in regression analysis, involves either examining the data or relying on theories to identify salient attributes. This study exploits the vast empirical work on the MMP data and uses several attributes that have been shown to determine migration behavior (e.g., in Massey and Espinosa 1997).

The attributes, listed in Table 1, include individuals' demographic characteristics (whether they are household heads and/or male, years of education, and occupation), household wealth (property, land, and businesses owned), prior migration experience (whether they migrated in Mexico, number of migrants to the US and of residents in the household, and proportion of individuals who have ever migrated in their community), and community characteristics (proportion working in agriculture, proportion self-employed, proportion earning less than the minimum wage, and whether the community is in a metropolitan area).

The average values for these attributes differ significantly between migrants and non-migrants. For the sake of comparison, both groups are observed on the survey year in each community. (In subsequent cluster analysis, migrants are observed on the year of their first US trip.) Compared to non-migrants, migrants are more likely to be household heads and male, to have higher levels of education, and to work in agriculture, manufacturing, or service occupations, rather than being unemployed. They live in wealthier

TABLE 1 Sample characteristics of migrants and non-migrants in 124 Mexican communities

Variable	Migrants	Non-migrants
Demographic characteristics		
Proportion household head	0.28	0.12
Proportion male	0.72	0.45
Years of education	6.86	5.97
Agricultural occupation	0.20	0.07
Manufacturing occupation	0.31	0.10
Service occupation	0.22	0.12
Unemployed	0.19	0.64
Other[a]	0.08	0.07
Household wealth		
Number of rooms in properties owned	4.21	3.61
Log of land value (US$ in 2000)	3.12	2.15
Number of businesses owned	0.41	0.37
Migration experience		
Proportion migrated within Mexico	0.22	0.17
Number of US legal residents in household	0.48	0.13
Number of migrants to US (non-residents) in household	1.81	0.72
Proportion ever migrated in community	0.19	0.13
Community characteristics		
Proportion in agriculture	0.28	0.24
Proportion self-employed	0.32	0.30
Proportion earning less than minimum wage	0.38	0.34
Proportion located in metropolitan area	0.41	0.50
N (persons)	17,049	107,838

NOTE: Migrants are individuals who have migrated at least once prior to the survey year. Non-migrants are individuals who have never migrated. Means for migrants and non-migrants differ significantly ($p<0.05$, two-tailed test) for all variables.
[a]Includes professionals, technicians, administrators, and persons working in education or the arts.
SOURCE: MMP survey data (see text).

households with ties to US migrants, and in poor and rural communities that contain a high proportion of self-employed individuals and agricultural workers.

Similar to the evidence in prior work, the significant differences between migrants and non-migrants observed here establish the relevance of the selected attributes for migration. Also relevant for migration, but not included in the cluster analysis, are indicators that capture important economic or policy events, like Mexico's sharply rising inflation or interest rates in the 1980s or the passage of IRCA in 1986. These events introduced external shocks to the migration system and typically shifted the magnitude or composition of the migrant stream. Hence, they allow evaluation of the migrant clusters, which, if substantively valid, should display a temporal pattern reflecting these shifts. We explore this connection in later analyses.

The selected attributes in this study are measured on different scales. About half are binary (e.g., sex, occupation), a few are counts (e.g., number of properties owned or years of education), and the rest are continuous. Clustering methods are typically sensitive to scaling of attributes, which determines the importance assigned to a particular attribute. To avoid an arbitrary weighting of attributes, we dichotomize each non-binary attribute so that the values above the median are converted to 1 and those below it to 0. This strategy standardizes the range of attributes, and has demonstrated superior performance in prior studies compared to other scaling methods that standardize the variance of attributes (Milligan and Cooper 1988). Similar to past work, we find that the attributes standardized to the same scale (but not the same variance) lead to the most well-separated and substantively meaningful clustering solution in the MMP data (comparisons available upon request).[4]

Choosing an algorithm. Clustering algorithms use a set of attributes to divide the data into a given number of groups (or "clusters") so that the cases in a group are as much alike as possible. The output is typically a cluster membership for each case and a centroid for each cluster that represents the "mean" (or average) of the cases in that cluster. We employ the popular K-means method, a classic clustering algorithm that iterates between computing K cluster centroids by minimizing the within-cluster variance and updating cluster memberships (Hastie, Tibshirani, and Friedman 2009).

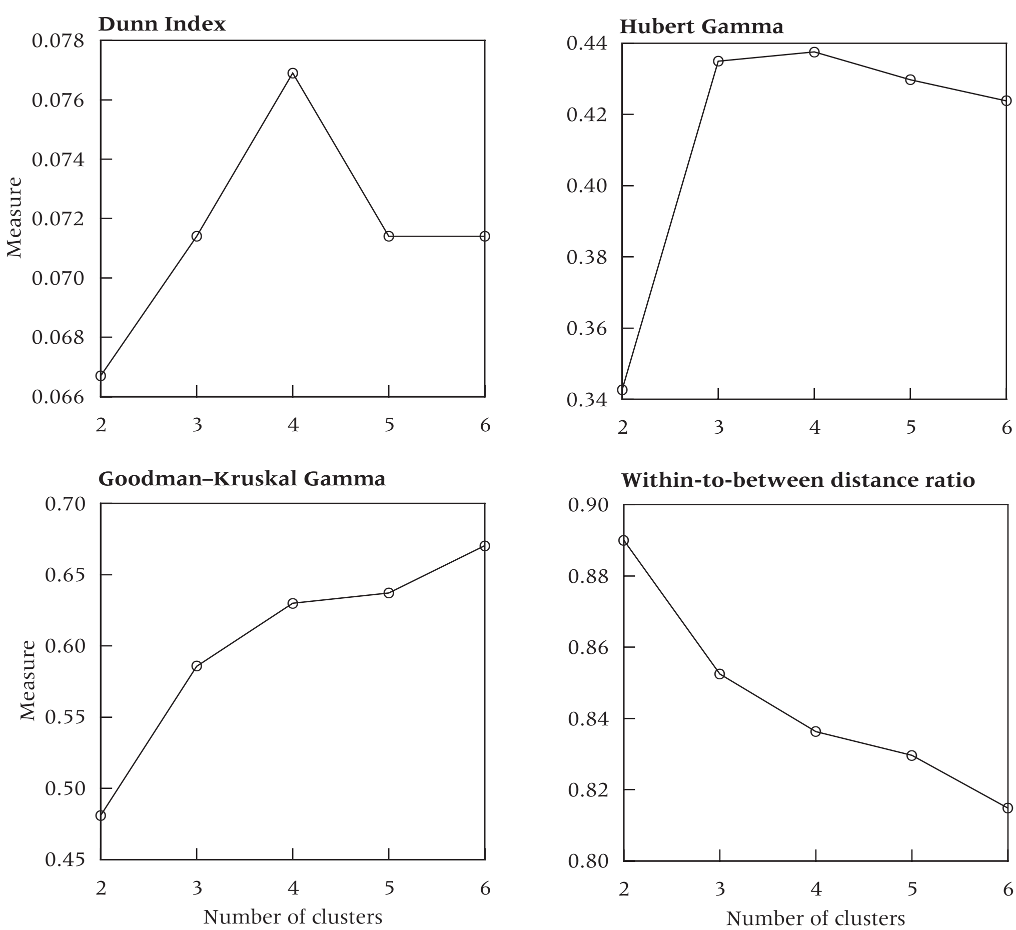
The K-means method makes no assumptions about the data structure and thus has been generically applied to a diverse set of problems. Alternative methods typically assume a hierarchical clustering structure or rely on a probabilistic model of the data. The hierarchical approach is useful if such a structure is substantively expected (e.g., evolutionary trees in biology), which is not the case in this study. The model-based approach is advantageous if the data conform to a probabilistic model, and has proven useful in low-dimensional data sets. Yet, experience shows that the available software implementations of the model-based approach perform poorly with large and high-dimensional data sets like the MMP. For substantive and practical reasons, we use the K-means algorithm implemented in Matlab® software (Matlab 2010, version 7.6). This algorithm, in addition to being generic and fast, is equivalent to the model-based approach for certain probabilistic models of the data.

Choosing a similarity measure. All clustering algorithms rely on a measure of similarity or dissimilarity to assess how "close" cases are to one another in the attribute space. In fact, choosing this measure is far more consequential for discovering the clustering structure in data than is specifying the algorithm itself (Hastie, Tibshirani, and Friedman 2009). Although there are no generic guidelines, researchers typically base their decisions on the nature of the data and the substance of the question.

This study uses the city block distance to assess how close migrants are to one another in various demographic, economic, and social attributes. This measure aptly deals with binary data and reflects our substantive preference to treat two individuals who share a trait (e.g., low education) as equally similar to one another as two individuals who both lack the trait. For every pair of individuals i and j, the city block distance, d_{ij}, is the sum of the absolute differences in the values x_{il} and x_{jl} of each attribute $l = 1,\ldots,p$,

$$d_{ij} = \left(\sum_{l=1}^{p} \left| x_{il} - x_{jl} \right| \right) \quad (1)$$

FIGURE 1 Cluster validation measures across number of clusters



NOTE: See discussion in text.

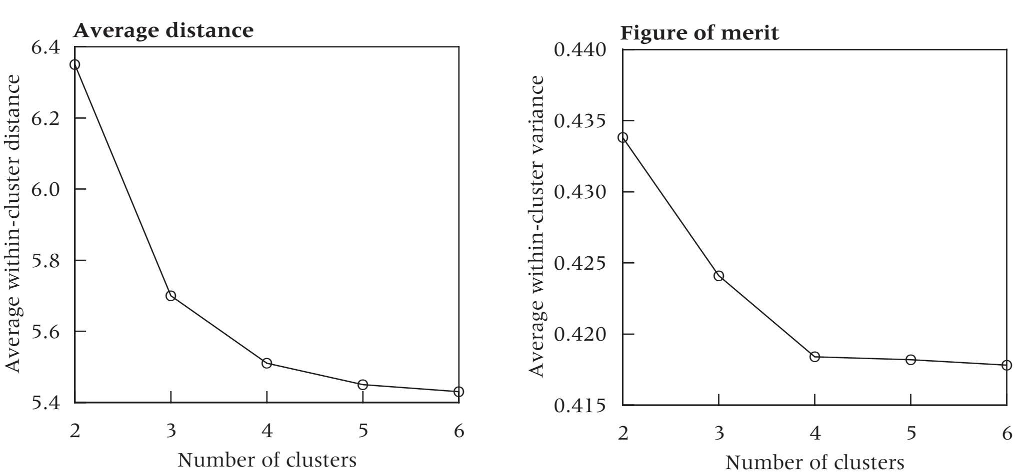
Choosing the number of clusters. A final step in cluster analysis requires the researcher to supply the number of clusters, K, to the K-means algorithm. By construction, this algorithm locates K clusters even when no such structure exists in the data. To avoid obtaining artificial partitions, researchers use cluster validation measures to choose the optimal number of clusters. This process is similar to model selection in regression analysis, where researchers use the likelihood ratio or another criterion to select the best and most parsimonious model for the data.

This study uses six cluster validation measures to estimate the number of clusters in the MMP data. These measures are implemented in the *clValid* and *fpc* packages in the R software (Brock et al. 2008; R Development Core Team 2010). The four panels in Figure 1 present four measures plotted against the number of clusters ranging from two to six. For the Dunn Index and Hubert Gamma in the upper panels, and the Goodman–Kruskal Gamma in the lower-left panel, higher values indicate higher cluster quality. For the within-to-between distance ratio in the lower-right panel, lower values indicate higher cluster quality.

The two measures in the upper panels obtain their highest value for the 4-cluster solution. The two measures in the lower panels reach optimal value for the 6-cluster solution, but the 4-cluster solution is not too far off. In fact, for both measures, the 4-cluster solution corresponds to an "elbow," where the index value increases (or decreases) steeply through the 3- and 4-cluster solutions, and only gradually thereafter.

Two additional measures, plotted against the number of clusters in Figure 2, capture the stability of clusters to changes in the attribute space. Spe-

FIGURE 2 Cluster stability measures across number of clusters

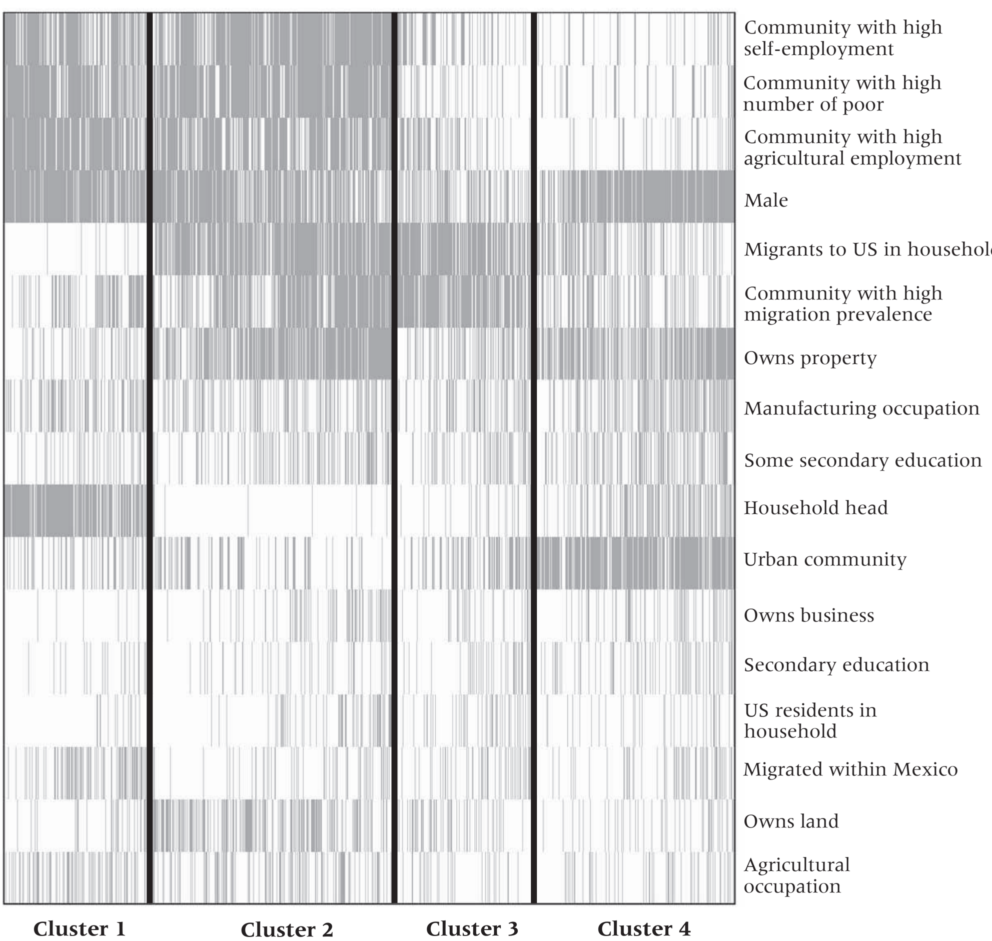


NOTE: See discussion in text.

cifically, both the average distance and the figure of merit evaluate whether the clustering solution remains stable if attributes are removed one at a time. For both measures, lower values indicate more stable clustering solutions. The 6-cluster solution yields the best score in both cases, but the 4-cluster solution is a close contender, being located at a point where the slope of the curve changes dramatically.

On the basis of these results, and given a preference for parsimony, we choose the 4-cluster solution, which is optimum for two measures and reasonable for the remaining four. This broad agreement across various measures is rare in clustering applications and increases confidence in the validity of the results.

FIGURE 3 Heat map of migrant attributes by cluster membership



NOTE: The heat map color codes the attributes (rows) of all migrants (columns). Gray indicates the presence of the attribute, and white indicates its absence. The vertical black lines separate the four clusters identified with cluster analysis.

Assessing the validity of results. Another useful way to assess the clustering results is to draw a cluster heat map. Imagine that each individual is represented by a vertical column of rectangles, where each rectangle corresponds to an attribute. A gray rectangle denotes the presence of an attribute, and a white one shows its absence. If the columns for all individuals are stacked side by side, while keeping the individuals in the same cluster together, one ends up with a heat map, an ingenious display of the entire data matrix (17 attributes x 17,049 individuals) along with the cluster structure. Figure 3 shows the heat map for the MMP data generated by the *heatplus* package in the R software. The rows show the attributes that are ordered in such a way that the correlated attributes are close to one another. The columns represent the individual migrants. The black vertical lines separate the four clusters.

Each cluster contains migrants on their first trip to the United States, but with visibly distinct characteristics. Migrants in cluster 1 are mostly male household heads; those in cluster 2 typically own many assets. Both groups live in poor rural communities. Migrants in cluster 3 are mostly females and live in households or communities with former migrants to the US. Those in cluster 4 are relatively well educated and live in urban communities.

Several attributes in the heat map are highly correlated with one another. Communities with a high number of poor individuals also have high levels of self- or agricultural employment. Households with former migrants to the US are typically located in communities with high levels of migration. Individuals with a high level of education are likely to live in urban communities. It is precisely because of these correlations that our data fall into distinct groups, providing fertile ground for cluster analysis.

Results

Interpreting the clusters

The four columns in Table 2 present the mean values of attributes in each of the four clusters. The last two rows show the number and proportion of migrants in each cluster. The attributes are measured on migrants' first trip to the United States. For each attribute, the highest cluster mean is shown in boldface and differs significantly from the value closest to it in all cases but one (migrants to the US in the household). We interpret these values in light of migration theories and label each cluster as a specific migrant type.

The first cluster contains the highest percentage of men (90%), household heads (83%), and migrants with no education (40%, not indicated in the table, *n.i.* henceforth) across all clusters. The group also includes the highest share of agricultural workers (31%) and the lowest share of wealthy migrants overall. Only 19 percent of migrants in this group own property, 11 percent own some land, and 5 percent own a business. About a third have also mi-

TABLE 2 Migrant characteristics by cluster membership in 124 Mexican communities (proportion within each cluster)

Variable	Income maximizers	Risk diversifiers	Network migrants	Urban migrants
Demographic characteristics				
Household head	**0.83**	0.02	0.07	0.32
Male	**0.90**	0.73	0.38	0.80
Some secondary education	0.17	0.24	0.24	**0.30**
Completed secondary education	0.08	0.09	0.12	**0.17**
Agricultural occupation	**0.31**	0.24	0.11	0.13
Manufacturing occupation	0.31	0.29	0.23	**0.39**
Household wealth				
Owns property	0.19	**0.76**	0.33	0.67
Owns land	0.11	**0.38**	0.20	0.12
Owns business	0.05	**0.16**	0.11	0.14
Migration experience				
Migrated within Mexico	**0.33**	0.12	0.14	0.18
Any US legal residents in household	0.04	0.14	**0.17**	0.09
Any migrants to US (non-residents) in household	0.04	0.80	**0.81**	0.33
Community with high migration prevalence	0.34	0.60	**0.79**	0.29
Community characteristics				
High agricultural employment	**0.82**	0.74	0.27	0.12
High self-employment	0.69	**0.85**	0.27	0.10
High number of low earners	0.79	**0.83**	0.15	0.13
Located in metropolitan area	0.26	0.20	0.34	**0.81**
N (persons)	3,522	5,569	3,271	4,687
Percent of total migrants	21	33	19	27

NOTE: The highest mean value for each variable, shown in boldface, differs significantly from the value closest to it ($p<0.05$, two-tailed test) in all cases but one (migrants to the US in the household).

grated within Mexico. A small share has family ties to US migrants (4%) or residents (4%). A larger share (34%), but still small compared to two of the other clusters, lives in communities with high migration prevalence. Roughly 80 percent of migrants in this cluster lives in rural communities with high agricultural employment, and an equal share lives in communities where a high proportion of individuals earn less than the minimum wage.

A characteristic migrant in this first cluster is a male household head who has no education and, hence, no access to well-paid jobs in the local labor market. He lacks income-generating assets, such as land or a business, and lives in a poor rural community. Given his meager economic prospects at home, we posit that this person migrates primarily to increase his income and acts according to predictions of neoclassical economics theory. To reflect this correspondence, which we support with circumstantial evidence in subsequent analysis, we label this migrant and the group he represents an "income maximizer." The average income maximizer lacks the social ties to facilitate an international move; hence, he may migrate in Mexico first to raise the funds or acquire the experience necessary for a trip to the US.

The second cluster consists of the wealthiest migrants in the sample. Of these migrants 76 percent own property, 38 percent own land, and 16 percent own a business. Most of them have family ties to earlier migrants to the US (80%) and live in communities with high migration prevalence (60%). The majority are men (73%) and adult children (91 percent, *n.i.*), not heads, in the household. Forty percent (*n.i.*) of these migrants have primary education only, and about a third have some (24%) or complete (9%) secondary education. Eighty-five percent live in communities with high self-employment, and a commensurate proportion (83%) come from communities where a high proportion of individuals earn less than the minimum wage.

A representative migrant in the second cluster is the son of the household head and has only primary education. He lives in a poor community, where the assets of his household, a property and either a piece of land or a business, place him in the middle or upper wealth category. Given his substantial economic endowments, we posit that this person migrates to diversify the risks to those endowments in the context of Mexico's volatile economic climate. While the migrant, labeled a "risk diversifier" in line with the new economics theory, secures earnings in the United States, the other members of his household, typically the head, manage the roles of subsistence in Mexico. A risk diversifier is expected to migrate temporarily at times of high economic uncertainty. This expected pattern, which we demonstrate in subsequent analysis, is probably facilitated by the migrant's ties to earlier migrants to the US in the family or community.

The third cluster is distinct in including mostly female migrants (62%) who are well-connected to other migrants. Eighty-one percent have family ties to migrants to the US, 17 percent are connected to US residents, and 79 percent live in communities with high migration prevalence. Most of these migrants are the daughter (38%, *n.i.*) or wife (21%, *n.i.*) of the household head, have primary education only (38%, *n.i.*), and are unemployed (47%, *n.i.*). Few of them own any assets. About one in three owns property, one in five owns land, and only one in ten owns a business. Compared to the first two clusters, a lower share of these migrants (15%) live in poor communities, but a higher share (34%) are located in metropolitan areas.

A typical migrant in this group is the unemployed daughter of the household head. At least one member of her household, probably her father or husband, is a current or prior migrant to the US. Given that she is not economically active, but connected to other migrants, we posit that this person migrates to join her family members at the destination and label her a "network migrant." Network migrants, who follow social ties rather than economic incentives, are a crucial component of cumulative causation theory, which predicts migration flows that are progressively independent of the economic conditions that initiated them. We expect, and later show, that network migrants become especially prevalent when family reunification policies are in place in the United States.

The fourth cluster contains the highest percentage of educated migrants, who mostly work in manufacturing (39%) and live in urban metropolitan areas (81%). Most of them are male (80%) and twice as likely to be the adult children (60%, *n.i.*) rather than the heads (32%) in their households. About one-third of these migrants have started, and about one-fifth have finished secondary education. Sixty-seven percent of migrants in this cluster own property, and 14 percent own a business, the second highest share across the four clusters. About a third have family ties to migrants to the US, and a third live in communities with high migration prevalence. Only a small share lives in communities with high proportions in agriculture (12%), in self-employment (10%), or in communities with a high share of low-wage earners (13%).

The representative migrant in this cluster is the son of the household head, has some secondary education, and lives in an urban community. Given his education and place of residence, this migrant has access to more and better job opportunities than a typical migrant in the other clusters. He owns property, which provides him with economic security, but lacks risky assets like land or a business. He does not have any prior migrants in his family and does not live in a traditionally migrant-sending community. Based on this configuration, which is not anticipated in any individual-level migration theory, we call this person an "urban migrant" to underline one of his most distinguishing characteristics.

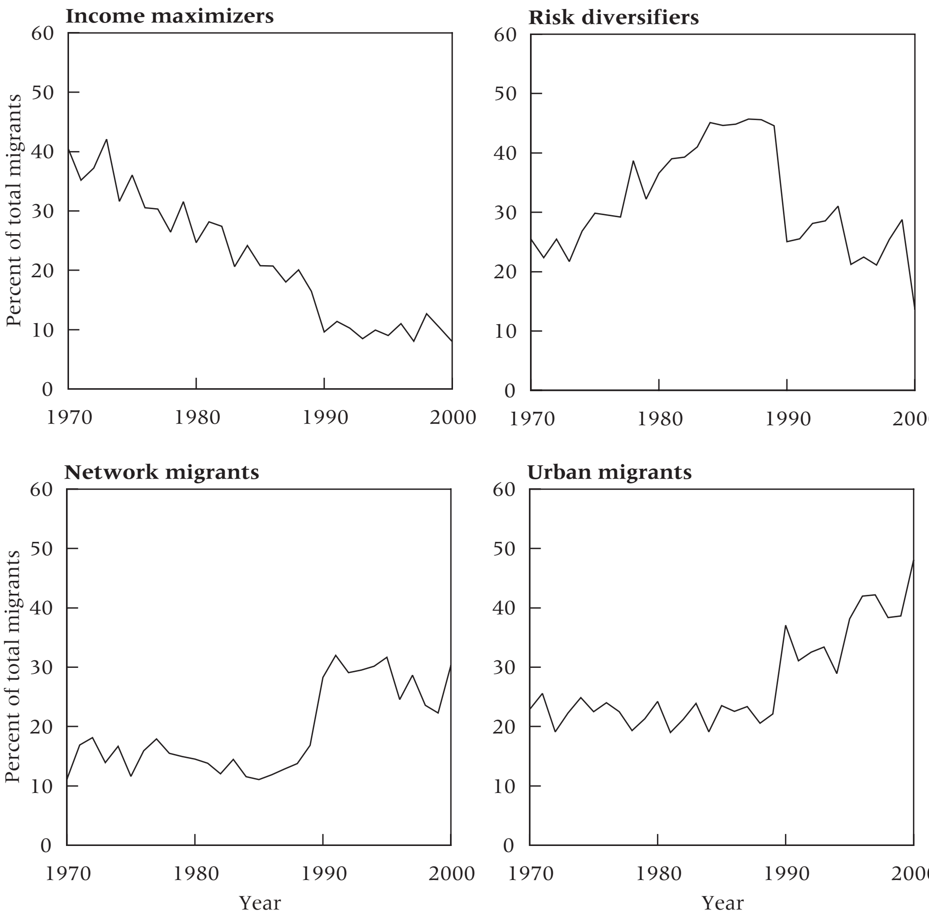
In the remainder of this article we first evaluate the temporal patterns in the prevalence of the four migrant types. We then consider the important economic and policy trends in the study period in order to justify the labels we have attached to the migrant types and to identify the contextual prerequisites for the emergence or dominance of those types.

Exploring temporal patterns

We identified the four migrant types based on migrants' own, household, and community characteristics on their first trip to the United States. In this process, we incorporated migrants observed at different time points into a single cluster analysis and deliberately excluded indicators for economic or policy trends that characterize the Mexico-to-US migration context. Despite the exclusion of these trends, we still obtained results that show a strong temporal pattern.

The four panels in Figure 4 show the percentage of migrants in each migrant type over time. (We focus on percentages rather than total numbers to account for the varying sample sizes over time.) Income maximizers, shown

FIGURE 4 Trends in the distribution of migrants by cluster



in the upper-left panel, comprise the majority (40%) of migrants in the early 1970s, but decline consistently in proportion over time and become the minority (10%) in the 1990s. Risk diversifiers, shown in the upper-right panel, increase in relative size through the 1970s and reach their highest level in the mid-1980s. Accounting for almost half of all migrants then, this group shrinks relative to other groups through the 1990s and contains only about one-fifth of migrants in 2000. Network migrants, displayed in the lower-left panel, show constant presence through the 1970s and 1980s, accounting for about 15 percent of all migrants. In the early 1990s, this group doubles in proportion, becoming a close second to the majority of urban migrants. Although accounting for about a fifth of migrants in earlier years, urban migrants, shown in the lower-right panel, increase to majority status in the early 1990s and make up about half of all migrants in 2000.

The figure displays a striking temporal order in which each migrant type prevails in a different period. Income maximizers characterize the 1970s, and risk diversifiers dominate the 1980s. Network migrants gain prominence in the early 1990s, and lag closely behind urban migrants, the increasingly dominant majority group. This order raises questions about the interpretation of group differences in Table 2. If each group is prevalent in a different period, then the differences between groups in attributes like education or urban origin may not signal inherent divisions among migrants, as one might have assumed, but instead reflect general trends in Mexico, like rising education levels or increasing urbanization. Put differently, an urban migrant may have higher education than an income maximizer, not because he represents a different migrant type, but because he is observed at a later period when education levels are generally higher in Mexico.

We investigate this possibility for two attributes, education and urban origin, that are most likely to change in the Mexican population over time. We find that, for each migrant type, recent cohorts have higher education than earlier cohorts. An average income maximizer has 4.7 years of education in the 1970s, which increases to 6.5 years in the 1980s and 6.9 years in the 1990s. An average urban migrant, by contrast, has 5.9 years of education in the 1970s, 7.8 years in the 1980s, and 8.3 years in the 1990s. Although the level of education rises consistently for both migrant groups over time, the difference between the two groups varies tightly around 1.2 years and remains statistically significant in each period.

A similar analysis reveals that migrants in more recent cohorts originate from larger communities than those who left earlier. An average migrant comes from a community of 95,000 inhabitants in the 1990s, compared to 52,000 in the 1980s and 40,000 in the 1970s. Despite this general trend, which is the result of growth in population and urbanization in Mexico, the differences across groups show remarkable stability. In each period, urban migrants come from larger communities than network migrants, who in turn live in larger communities than income maximizers or risk diversifiers. Hence, while each migrant group reflects the trends in the general population, it still retains its distinguishing character vis-à-vis the other groups. (These results are confirmed with regression analysis in a subsequent section.)

In the following section, we identify the contextual conditions that lead different migrant groups to become the majority in different periods, and hence suggest potential sources of the temporal variation in migrant characteristics.

Bringing in the context

During the study period 1970–2000, a number of economic and policy trends characterized the context of Mexico-to-US migration. We discuss these trends chronologically and consider their connection to the prevalence of different migrant types in the data. In Figure 5, we juxtapose four of these trends against the prevalence paths for the four migrant types and detect consistent patterns of co-variation that we describe below.

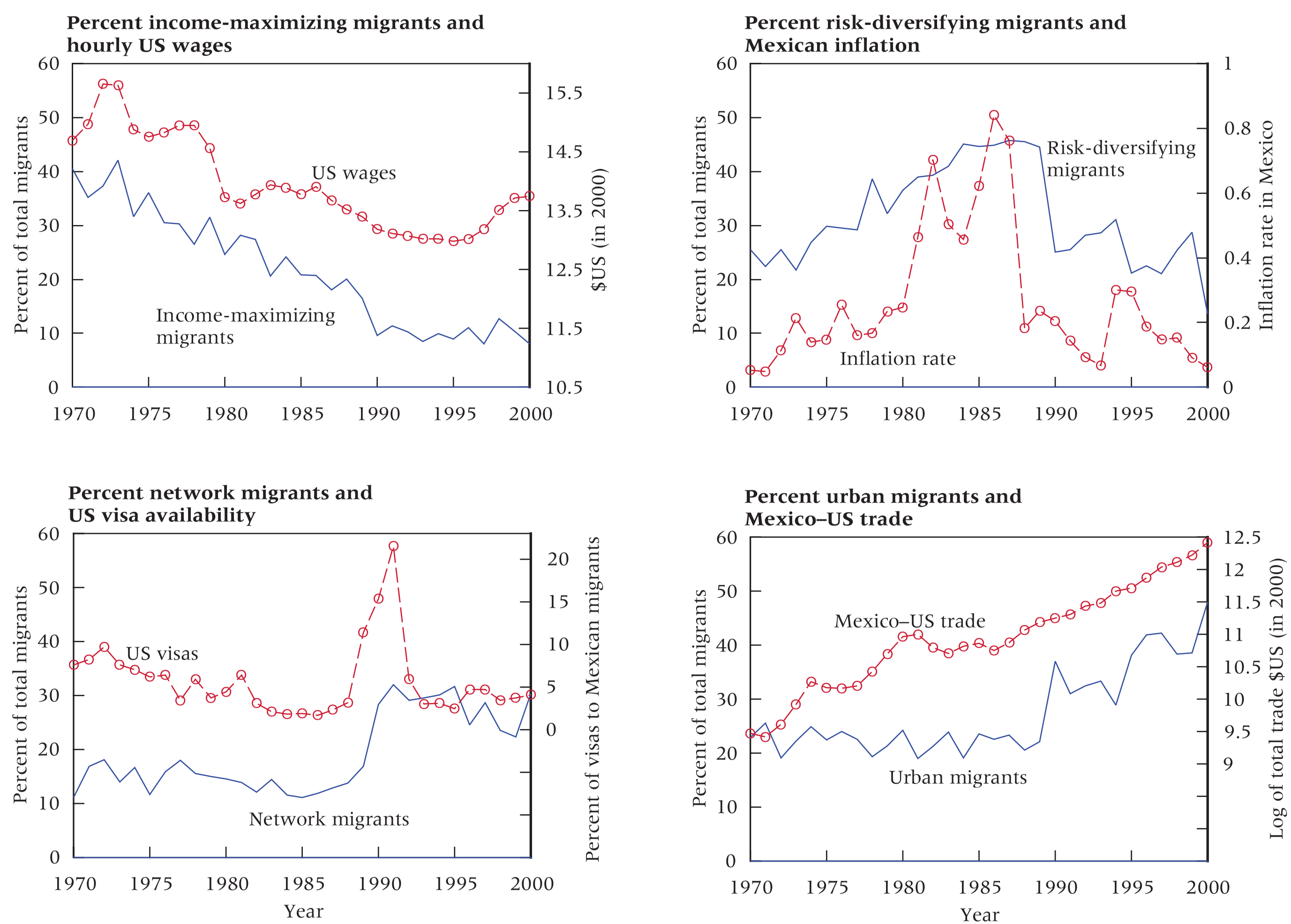
Starting in the 1960s, Mexico experienced a prolonged decline in agricultural productivity (Heath 1988; Martin 2003), which led to a shortage of job opportunities (Roberts, Frank, and Lozano-Ascencio 1999) and the worsening of living standards for low-income rural families (Reyes-Heroles 1983). Through the 1970s, the reductions in arable land and declining prices of agricultural products swept the country into a deepening agricultural slump (Papail and Arroyo 2004). The increasing mechanization of agriculture in this period contributed to further displacement of farm workers, most of whom migrated to internal or international destinations (Arroyo 1989; Durand and Massey 1992; Yates 1981). Workers who migrated to the United States filled farm jobs, which, following the end of the Bracero program, had come to be defined as immigrant jobs that were socially unacceptable to the US citizens (Massey, Durand, and Malone 2003; Piore 1979).

In our MMP data, the majority of migrants in the 1970s are poor and uneducated agricultural workers from rural communities. As the above description suggests, this group, labeled income maximizers, was particularly strained by the economic conditions in Mexico at the time. In neoclassical economics theory, income maximizers are expected to migrate from a low-wage origin to a high-wage destination to increase their earnings. This proposition implies that the share of income maximizers in our sample should respond to changes in Mexican or US wages.

The upper-left panel of Figure 5 displays the percentage of income maximizers alongside average hourly US wages over time. The values for the former series are shown on the left-hand y-axis, and the values for the latter (converted to constant US$ in year 2000) are shown on the right-hand axis. The two trend lines follow a similar path and in fact are correlated at a very close +0.89. Income maximizers attain their largest share, comprising 40 percent of the sample, in 1970 when US wages are high, around $15 per hour. The share of income maximizers recedes to 30 percent of the sample in 1980 when US wages declined to $13.5 per hour, and eventually drops to 10 percent in 1990 when the US wages reached their lowest value of $12.5 per hour. A similar pattern appears if we juxtapose the percentage of income maximizers against the US-to-Mexico ratio of wages (not shown). The two trend lines closely follow one another and correlate at +0.64.

The close affinity between the proportion of income maximizers and US wages not only confirms the label we have assigned to this group, but also suggests that predictions of neoclassical economics hold in the Mexico–US context for a specific group of individuals and under specific economic conditions. This observation reaffirms our initial claim that migration theo-

FIGURE 5 Trends in the economic and political contexts of Mexico-to-US migration



ries are conditional statements and should be treated as such in empirical applications.

Along with the decline in agriculture, a number of other conditions in Mexico changed in the late 1970s. In 1976, after two decades of stability, the Mexican peso was devalued by 45 percent against the dollar. In the early 1980s, oil prices plummeted globally, causing a sharp decline in Mexico's revenues from oil exports. This decline, coinciding with two additional peso devaluations in 1982, led to a significant drop in wages and a sharp increase in inflation and interest rates (Meza 2006). These conditions had a substantial negative impact on the Mexican middle class (Escobar and Roberts 1991). First, the 1982 devaluations caused a shift in Mexico's development model and led to the state's withdrawal from the agriculture sector and to reductions in agricultural subsidies (Alba and Potter 1986). As a result, middle-income rural families who owned small agricultural plots faced serious setbacks. Similarly, middle-income urban families experienced steeper wage declines than low-income families. In the city of Oaxaca, for example, families in the top 40 percent of the income strata lost 59 percent of their income from 1977 to 1987, while families in the bottom 60 percent lost only 14 percent (Selby 1989).

In our data, the majority of migrants in the 1980s originated from relatively wealthy households in rural communities. These migrants, called risk diversifiers, experienced the pronounced effect of the economic downturn and moved to the United States, presumably to diversify the risks to their subsistence. If these migrants were indeed diversifying risks, then the timing of their move to the United States should correspond to periods of economic uncertainty in Mexico, captured with indicators like inflation or interest rates.

The upper-right panel of Figure 5 juxtaposes trends in the percentage of risk diversifiers against the Mexican inflation rate. The two trend lines closely follow one another and are strongly correlated (+0.71). Risk diversifiers attain their largest share, making up nearly half of the sample, in 1985 when the Mexican inflation rate is at its highest value of 60 percent. As the inflation rate drops to 10 percent in 1990, the share of risk diversifiers plunges to 25 percent. The strong correlation between the share of risk diversifiers and the Mexican inflation rate suggests that the predictions of the new economics theory hold particularly for this migrant group.

In addition to signaling the start of the economic recession in Mexico, the early 1980s was a period of political backlash against undocumented migration in the United States, which culminated in passage of the Immigration Reform and Control Act in 1986 (Massey, Durand, and Malone 2003). IRCA, on the one hand, increased border enforcement and sanctions against employers hiring undocumented migrants. On the other hand, it legalized 2.3 million Mexican migrants in the United States. While the employer sanctions discouraged migration of men for work (Bean et al. 1990), the legalizations increased migration by women and dependent children for family reunification (Hondagneu-Sotelo 1994).

In the MMP sample, network migrants, mostly women joining their families in the United States, although present throughout the study period, proliferated in the years following IRCA. These migrants, mobilized by social ties rather than economic pressures as predicted by cumulative causation theory, became the second-largest group in 1990, comprising about 30 percent of all migrants, a share they maintained through the decade.

This pattern is observed in the lower-left panel of Figure 5, which shows side by side the percentage of network migrants and the percent share of available visas going to Mexican migrants. The two lines spike in the same period immediately following IRCA. Although the percentage dropped after 1990, network migrants retained their level because of higher incentives for the relatives of newly legalized Mexicans to migrate as well, albeit without documents. The correlation between the two lines is modest (+0.28) because of the pent-up demand that led to a response that is highly skewed to the first years of the policy change, and because the percent of visas going to Mexican migrants is related only to network migrants legally admitted, not including those who are undocumented.

The passage of IRCA, ironically, coincided with Mexico's admission into the Generalized Agreement on Tariffs and Trade (GATT), which accelerated trade flows between Mexico and the United States at an unprecedented rate. The implementation of the North American Free Trade Agreement in 1994 further promoted economic integration between the two countries. The *maquiladora* program, for example, instituted in 1965 in the border Mexican states to provide cheap labor to US firms, expanded from 600 plants employing 120,000 workers in 1980 to 4,000 plants employing 1.3 million workers in 2000 (Durand, Massey, and Zenteno 2001). This expansion attracted internal migrants to the border states in Mexico through the 1990s. Some of these internal migrants, especially indigenous Mixtecs and Oaxacans, continued on to become migrants to the United States (Zabin et al. 1993).

The Mexican economy, which appeared solid at the signing of NAFTA, experienced an economic crisis in December 1994. Following a peso devaluation, the country defaulted on its foreign debt and, within a year, saw its GDP shrink by 6 percent and its unemployment rate double (Meza 2006). Around the same time, the United States was in the midst of the longest sustained period of job growth in its history. The economic differentials between the two countries once again ensured the continued flow of migrants. In contrast to earlier years, migrants in the post-NAFTA and post-crisis era included many educated professionals who were admitted for short-term employment. From 1994 to 1997, the number of Mexicans admitted for temporary work (under the H visa program) tripled, reaching 37,000 persons per year (Durand, Massey, and Zenteno 2001).

In the MMP sample, the majority of migrants in the 1990s were relatively well educated, worked in manufacturing, and lived in urban areas. Labeled as urban migrants, the specific configuration of this group is not anticipated in any individual-level theory of migration. A number of studies, however, have noted the increasing prevalence of migrants from urban areas in the Mexico-to-US stream in the late 1980s and 1990s (Roberts and Hamilton 2007; Flores, Hernández-León, and Massey 2004; Hamilton and Villarreal 2011), attributing this pattern to economic downturns (Cornelius 1991), increasing urbanization (Durand, Massey, and Zenteno 2001), and macroeconomic transformations prompted by foreign investments (Lozano 2001). In the most comprehensive study to date, Hernández-León (2008) showed that the increasing numbers of migrants from metropolitan areas can be understood within the context of the economic restructuring in Mexico brought on by the shift in the country's development model and the implementation of NAFTA. These changes eliminated the safety nets for skilled working-class individuals, devalued their skills by transforming the industrial composition, and prompted them to resort to international migration as a coping strategy.

In a related line of thought, the rise of urban migrants can be explained by globalization arguments, which predict increasing migration flows with growing economic, cultural, and ideological linkages between countries (Sassen 1988, 1991). Well-educated individuals in urban areas, the typical migrants making up the urban stream in the MMP sample, may be the first to respond to these linkages. If that is the case, the proportion of urban migrants should increase with expanding economic ties between Mexico and the United States, captured, for instance, by data on trade flows. Such a link would also validate Hernández-León's hypothesis, since the periods of increasing economic ties to the US (e.g., due to GATT and NAFTA) overlap with periods of economic restructuring in Mexico.

The lower-right panel of Figure 5 compares trends in the percentage of urban migrants and the logarithm of Mexico–US trade, thus providing preliminary evidence of this link in the MMP data. The two series, correlated at +0.77, showed little movement until 1986, when both began to move rapidly upward. Urban migrants became the largest group in 1990 and continually increased thereafter, mirroring the rapid expansion in Mexico–US trade. Although this pattern suggests the plausibility of the globalization and economic restructuring hypotheses, both of which are related to world systems theory, more analysis is necessary to connect these ideas to the specific migrant configuration observed in the data.

The descriptive results in Figure 5 are corroborated by an OLS regression of the annual percentage of each migrant type in the overall population on all macroeconomic indicators (US wages, Mexican inflation rate, visa availability, and Mexico–US trade). In each case, the selected macroeconomic indicator for a given group (e.g., US wages for income maximizers) has the highest effect on that group compared to the other groups and compared to the other indicators for that group (which typically remain insignificant). The R^2 values range from 0.22 to 0.71. (Results are available on request.)

Linking empirical patterns to the emergence of migration theories

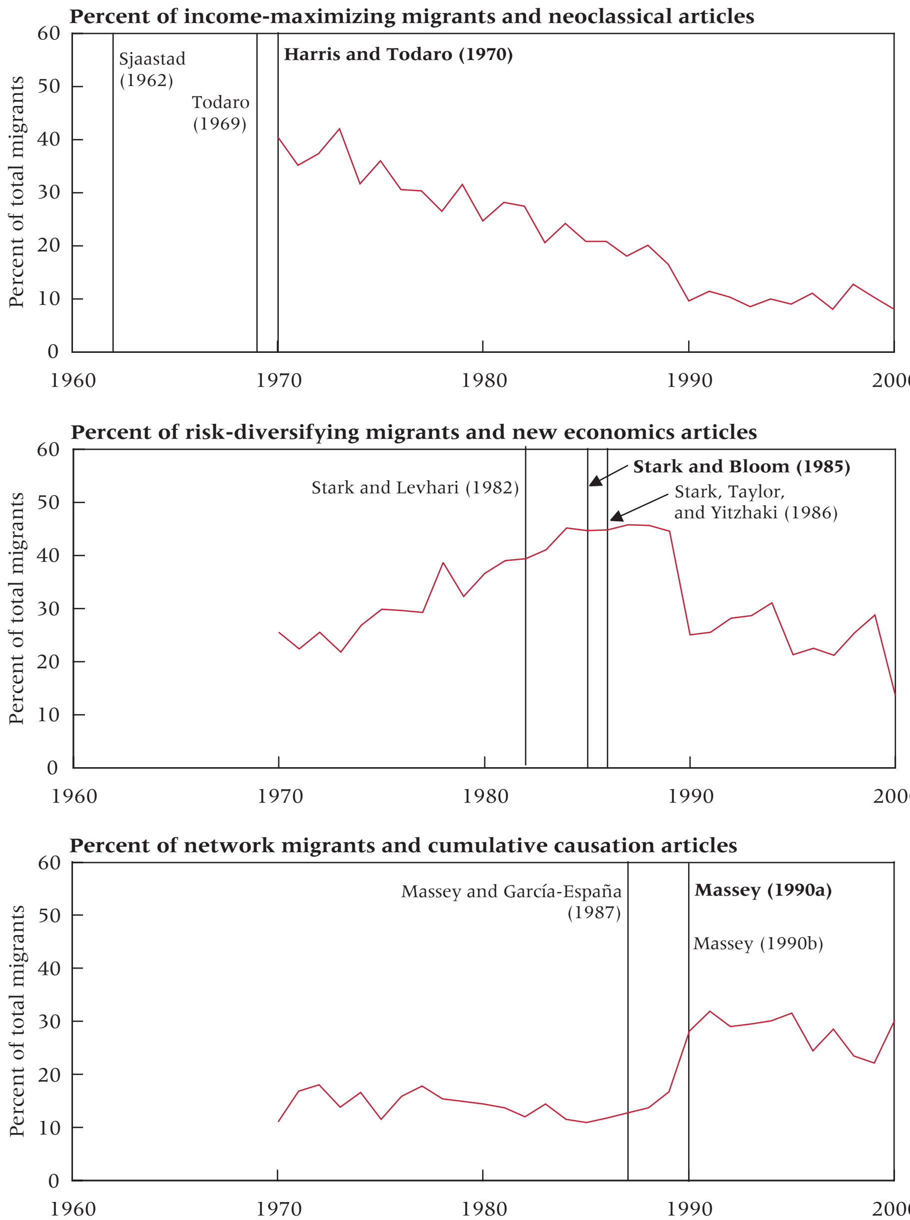
The temporal patterns discussed above suggest that each migrant type, corresponding to a distinct theoretical narrative, gains prevalence under specific economic, social, and political conditions. Income maximizers, representing neoclassical economics, were most prominent in the 1970s when US wages were at their highest level. Risk diversifiers, personifying the new economics theory, gained the majority in the 1980s when the Mexican inflation rate was at its peak. Network migrants, symbolizing cumulative causation theory, achieved their highest proportion in 1990s when visa availability was at its highest. We do not include urban migrants in the following analysis since the specific configuration of this group is not elaborated by any theoretical perspective, although, as we noted earlier, its temporal pattern seems to correspond to general trends brought on by globalization and Mexican economic restructuring.

Revealing a well-defined pattern, the temporal order of the prevalence of the three migrant types is reflected in the temporal order of the emergence of theories on which these types are based. The three panels in Figure 6 show the proportion of income maximizers, risk diversifiers, and network migrants. The vertical lines in each panel indicate the publication date of the three most frequently cited articles in three theoretical perspectives: neoclassical economics, new economics of migration, and cumulative causation.

Following two initial articles by Sjaastad (1962) and Todaro (1969), Harris and Todaro wrote the most-cited article of the neoclassical perspective in 1970 (shown in boldface in the figure), when income maximizers dominated the Mexico-to-US migrant stream. Similarly, Stark and Levhari (1982), Stark and Bloom (1985), and Stark, Taylor, and Yitzhaki (1986) published the first articles launching the new economics of labor migration around the time risk diversifiers became the majority among migrants in the MMP sample. Finally, Massey introduced cumulative causation theory in 1990 with two simultaneous publications, closely following his earlier work with García-España in 1987, when network migrants proliferated in the Mexico-to-US flows.

This temporal pattern suggests that different migration theories depict the dominant empirical trends in the world's largest international migration flow around the period in which they were developed, although they may not have been developed specifically for that purpose. In fact, the neoclassical model of migration can be seen as an application of Mincer's (1958) human capital model prominent in economics at the time. Similarly, the new economics model is an extension of the risk-diversification paradigm popularized

FIGURE 6 Trends in the distribution of migrants across clusters and publication dates of corresponding theories of migration



NOTE: Each graph shows the publication dates of the three most-cited articles for the corresponding theory. The top-cited article is in boldface. Citation data are from the Social Science Citation Index (accessed December 2009).

in finance by Markowitz (1959) and Sharpe (1964).[5] Cumulative causation theory follows from earlier work that linked social networks to chain migration (MacDonald and MacDonald 1964). But, because these theories reflect the empirical trends of their time, even if incidentally, they are likely to be cited more often than other research.

From descriptive results to testable hypotheses

The results presented so far yield a useful typology of migrants with a meaningful temporal pattern that is correlated with trends in the economic, social, and political context of Mexico-to-US migration, and with the temporal ordering of the prominent migration theories. Because these analyses only characterize the variation in migrants, below we raise and address three concerns that potentially challenge our interpretations.

First, the characteristics that differentiate among migrant types may not be important for differentiating between migrants and non-migrants. Put differently, these characteristics may not have an independent effect on migration, or their effect may not vary across migrant groups as one would expect. To investigate this point, Table 3 presents five logistic regression models of first Mexican migration to the US. The first model is run on a pooled sample of migrants and non-migrants, while the other four are run on samples containing a specific migrant group and non-migrants. Individuals are observed annually from age 15 through the year of their first migration to the US (for migrants) or the year of the survey (for non-migrants). The models include the individual, household, and community characteristics used in the cluster analysis as well as the contextual indicators presented in Figure 5, and they correct for the multiple observations at the individual level. (Indicators for the levels of agriculture and self-employment and the proportion earning less than minimum wage in the community are excluded because of their high correlation (>0.70) with the indicator for metropolitan location.)

The signs of the coefficient estimates for each migrant type are consistent with the earlier descriptions of these types. Individuals are more likely to become income-maximizing migrants, for example, if they are the household head and male and if they have no education and own no property or business. By contrast, individuals are more likely to become risk-diversifying migrants if they are not the household head and if they own land and property. The estimates for the macroeconomic indicators also show the expected patterns: the coefficient for hourly US wages obtains its highest value for income maximizers, while the coefficient for the inflation rate is largest for risk diversifiers. Similarly, the availability of visas has its largest effect on network migrants, whereas Mexico–US trade mainly influences urban migrants. Thus, the same set of socio-demographic and economic variables has different effects on the migration propensities of each group. Crucially, these differential effects remain hidden in the pooled model. The counter-effects of land values on risk diversifiers versus urban migrants, for example, offset one another in the pooled model, yielding an insignificant coefficient. Similarly,

TABLE 3 Estimates from a logistic regression model of first Mexican migration to the US by cluster membership

		By cluster membership			
	All migrants	Income maximizers	Risk diversifiers	Network migrants	Urban migrants
Demographic characteristics					
Age	–0.06**	–0.08**	–0.06**	–0.05**	–0.05**
Household head	0.52**	3.09**	–2.59**	–0.62**	0.68**
Male	0.78**	1.11**	1.16**	–0.31**	1.22**
Primary education	0.08**	–0.03	0.07	0.14**	0.12*
Some secondary education	0.08**	–0.15*	0.03	0.18**	0.21**
Completed secondary education	–0.09**	–0.46**	–0.38**	0.10	0.11
Agricultural occupation	0.67**	0.66**	0.86**	0.77**	0.52**
Manufacturing occupation	0.89**	0.79**	1.02**	0.98**	0.97**
Service or other occupation	0.55**	0.65**	0.69**	0.43**	0.45**
Household wealth					
No. of rooms in property owned	–0.02**	–0.20**	0.04**	–0.13**	0.03**
Logarithm of value of land (US$ in 2000)	0.001	–0.007	0.03**	–0.003	–0.04**
Owns business	–0.15**	–0.51**	0.01	–0.13*	–0.18**
Migration experience					
Migrated within Mexico	0.22**	0.44**	0.51*	0.16	–0.18**
Number of US legal residents in household	0.27**	0.12	0.28**	0.29**	0.21**
Number of migrants to US (non-residents) in household	0.52**	0.76**	0.46**	0.46**	0.50**
Community with high migration prevalence	0.59**	0.65**	0.29**	1.72**	0.51**
Community characteristic					
Located in metropolitan area	–0.50**	–5.37**	–5.20**	–0.61**	0.66**
Macroeconomic indicators					
Hourly US wages (US$ in 2000)	0.16**	0.26**	0.00	0.12*	0.17**
Inflation rate [0,1]	–0.11*	0.23*	0.31**	–0.95**	–0.34**
Availability of visas [0,1]	0.36	–1.27*	–0.89*	1.62**	1.01**
Log of total Mexico–US trade (US$ in 2000)	0.26**	0.14*	–0.18**	0.39**	0.44**
Intercept	–9.85**	–12.45**	–3.84**	–12.14**	–13.87**
N (person-years)	1,361,858	1,255,243	1,269,245	1,256,454	1,269,857

*p<0.05; **p<0.01 (two-tailed tests). Results are logit coefficients. Standard errors are corrected for clustering at the individual level. The sample for each model includes non-migrants (individuals who have never migrated) and the migrant group specified in the column heading. The reference group for education is individuals with no education; the reference group for occupation is individuals who are unemployed. Indicators for levels of agriculture and self-employment and the proportion earning less than minimum wage in the community are excluded because of their high correlation (>0.7) with the indicator for metropolitan location.

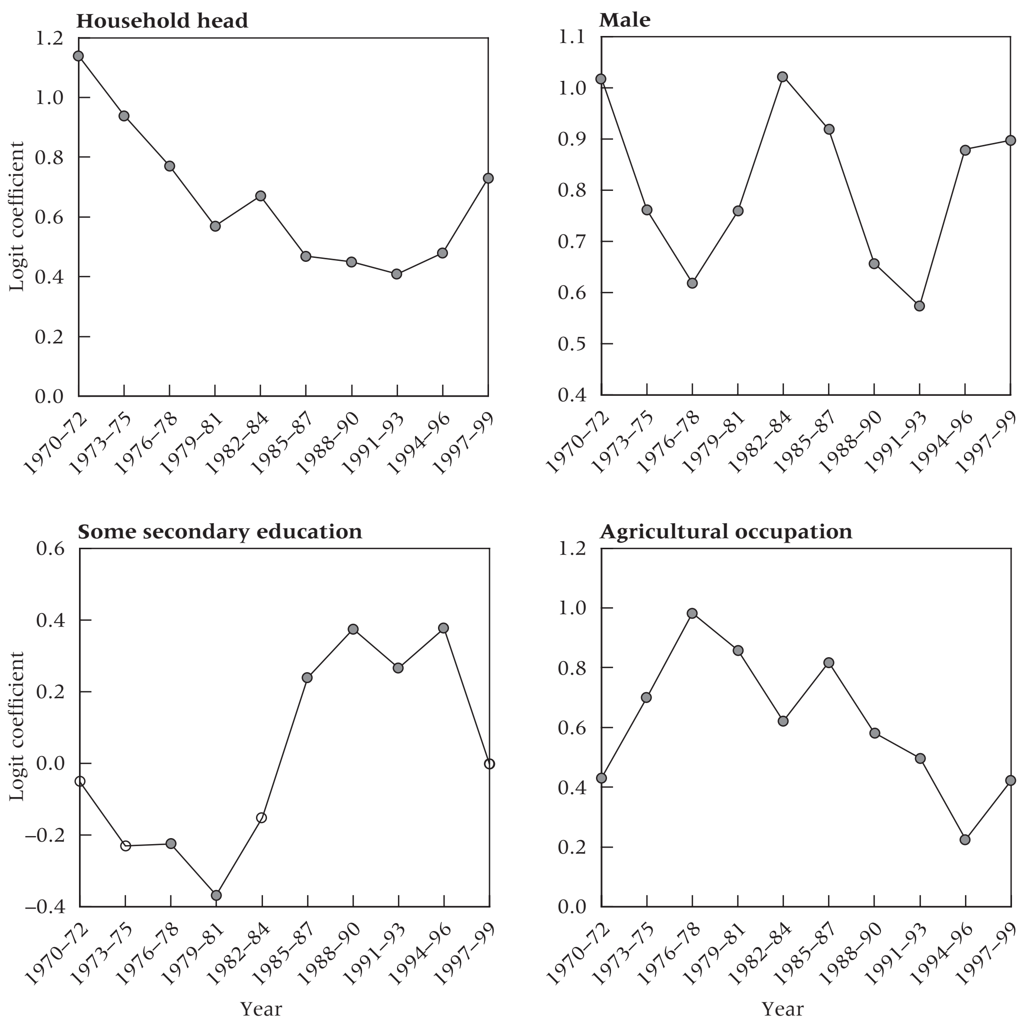
the differential effects of sex or education for each group disappear in the pooled model, where the coefficients simply reflect average effects based on relative group sizes. These results demonstrate that the characteristics used for identifying different migrant types have significant effects on migration behavior. The fact that these effects vary across groups suggests that diverse mechanisms shape the migration behavior of each group, mechanisms that are bound to be obscured in conventional pooled analyses.

To further confirm this last point, we address a second concern. Because each migrant type dominates in a specific time period, the differences observed among migrant groups may reflect shifts in the population composition over time, rather than shifts in the mechanisms underlying migration. For example, differences in the education levels of urban migrants and income maximizers may be attributed to increasing levels of education in Mexico's population, not to an increasing importance of education for migration to the US as we posit. The results in Table 3 partly address this concern. The different coefficient estimates of education for income maximizers and urban migrants suggest that these two groups do not just come from different pools, but that they are selected differently from these pools. (The results are similar if we introduce year fixed-effects to control for the temporal change in migration, thus sacrificing the identification of the macroeconomic indicators.)

To better define the trends in population composition, we ran logistic regressions of first US migration in the pooled sample using data from sliding three-year windows. Figure 7 shows the trends in the coefficient estimates of four key characteristics. The distribution of these characteristics in the migrant population is likely to change over time as a result of economic and political trends in Mexico. For example, migrants are more likely to include women, and consequently fewer household heads, in later periods because of the increasing participation of women in the labor market. Similarly, migrants are more likely to be educated, and less likely to work in agriculture, in later years because of increasing levels of education and urbanization in Mexico. But, because non-migrants experience similar changes, the shifts in population characteristics alone should not modify the *effects* of these characteristics on migration behavior over time. The results in Figure 7 show that the effects of being a household head, male, having some secondary education, and working in agriculture all changed considerably over time. The effect on migration of being male, for example, was highest in 1970–72 and 1982–84, but declined from 1985 to 1991 and increased thereafter. Similarly, the effect of secondary education was negative or insignificant (the latter depicted with white circles) before 1985, but increased sharply to positive values thereafter. These patterns suggest a changing selectivity of migrants that is independent of the changing characteristics of the population, and support our interpretation that the differences observed among migrant groups reflect shifts in the mechanisms and incentives underlying migration, not just shifts in population composition.

A third concern about the results is the extent of their usefulness beyond characterizing the heterogeneity in the sample on which they are based. Can one, for example, use the migrant types to develop testable hypotheses? Can

FIGURE 7 Trends in the coefficient estimates of four indicators in the pooled sample of migrants



NOTE: White circles indicate that the coefficient is not significant (p>0.05) in the time interval.

one then discover meaningful associations between these types and post-migration outcomes? To answer these questions, we consider five outcomes that characterize migrants' experiences in the United States: (1) total number of US trips, (2) undocumented entry, (3) receiving residency or citizenship, (4) being unemployed, and (5) wages. We hypothesize that migrants will differ significantly in these outcomes according to their cluster membership.

Given their short-term economic goals and the lower level of border enforcement at the time they predominantly migrated, income maximizers and risk diversifiers will make a higher number of total US trips compared to network or urban migrants. For the same reasons, these two groups will also be more likely to cross the border without documents. Because they are eligible to take advantage of family reunification policies, network migrants will have a higher likelihood of receiving US residency or citizenship compared to the other three groups. This group, however, will also be more likely to be unemployed since it comprises mostly women and children. Finally, given their high levels of education and involvement in manufacturing occupations, urban migrants will command the highest wages of the four migrant groups.

Table 4 presents results from five models to test these hypotheses. The first and last columns show coefficients from OLS models of the logarithm of total number of US trips and the logarithm of US wages during the first trip (in 2000 US$). The second, third, and fourth columns show odds ratios from logit models of whether the individual was undocumented on the first US trip, received residency or citizenship after the first trip, and was unemployed during the first trip. All models include year dummies. The models in the first and third columns also include an indicator for the time elapsed between the first trip and the survey year to control for differences among individuals in the opportunities for making US trips or obtaining legal status.

The results support all of our hypotheses. Network and urban migrants made 73 percent (exp(–0.31)) and 76 percent (exp(–0.27)) fewer trips in total compared to income maximizers (model 1). These two groups were also about 70 percent less likely to enter the US without documents (model 2). Network migrants were almost 10 times more likely to obtain legal status compared to

TABLE 4 Estimates from OLS and logistic regression models of various outcomes during or after first US migration

	(1) Log of total number of US trips	(2) Without documents during first US trip	(3) Received US residency or citizenship after first trip	(4) Unemployed during first US trip	(5) Log of wages during first US trip (US$ in 2000)
Cluster membership					
Income maximizer (reference)					
Risk diversifier	–0.15**	0.56**	7.50**	2.41**	–0.06*
Network migrant	–0.31**	0.36**	10.37**	7.90**	–0.01
Urban migrant	–0.27**	0.32**	5.74**	2.17**	0.10**
Years between survey and first US trip	0.002	—	1.21**	—	
Year dummies	yes	yes	yes	yes	yes
N (persons)	15,969	15,895	16,025	16,026	5,381
Adjusted or pseudo R^2	0.15	0.03	0.18	0.08	0.09

*p<0.05; **p<0.01 (two-tailed tests). Results in columns (1) and (5) are OLS coefficients; those in columns (2)–(4) are odds ratios.

income maximizers (model 3), but about 7 times more likely to be unemployed during the first trip (model 4). Finally, urban migrants earned about 10 percent more than income maximizers, their closest follower in terms of wages.

The results show that the four migrant types differ not only in their characteristics and the incentives underlying their migration, but also in their experiences in the United States. Our proposed typology thus provides unique insights for extending the explanatory potential of existing theories and for designing policies that target particular migrant groups to encourage certain post-migration outcomes.

Conclusion

Most questions in population research can be approached from a variety of theoretical perspectives. But in empirical applications, this diversity often gets lost. To use prevailing quantitative methods, such as regression analysis, researchers frame their questions around average differences—for example, between persons who display a specified behavior and those who do not—and reduce theories to competing sets of independent variables. If the corresponding variables identify statistically significant differences between groups, a theory is accepted; otherwise it is rejected. This strategy inevitably leads to either/or theoretical stances, rather than an emphasis on the complementarity of varying theories.

This study proposes a strategy to define and explain the theoretical diversity in theories of migration. Instead of focusing on differences between groups who do and do not exhibit a particular behavior, the proposed strategy calls attention to variability within a group of individuals who display the same behavior or outcome. Are there different paths that brought them there? Are these paths illuminated by different theories?

The empirical approach involves cluster analysis, a method commonly used in data-intensive fields like biology, physics, and computer science to identify subsets of cases with similar characteristics. In this novel application to social sciences, cluster analysis reveals distinct groups among individuals who share a behavior of interest, that is, migration. Each group is identified by a specific configuration of characteristics, and the experience of each group appears to be consistent with a specific theoretical account.

This approach provides a new perspective for understanding the migrant stream between Mexico and the United States. That stream, the largest in the world in the period under study (1970–2000), continuously increased, leading to a Mexican-born population in the US of 8.4 million by 2000 (Bean et al. 2001). During this period, the economic, social, and political conditions in the two countries changed substantially. These changes also shaped the character of the migrant stream, producing a Mexican population in the United States that is diverse in backgrounds and objectives. This diversity, identified in a number of theories developed in economics and sociology, is overlooked in quantitative applications that describe a typical narrative for an average migrant.

Applying cluster analysis to data from the Mexican Migration Project, covering some 17,000 first-time migrants over the period 1970–2000, this study identified four distinct types of migrants based on individual, household, and origin community characteristics. These types correspond to specific theoretical accounts and gained prevalence during specific time periods depending on the economic, social, and political conditions in both countries.

Earlier Mexican migrants consisted mainly of male household heads from rural areas with little education and few assets, who sought to increase their earnings by moving to the United States. Labeled as income maximizers, these migrants embodied the predictions of neoclassical economics theory. They remained the dominant migrant type when US wages were at their highest level in the early 1970s, and slowly declined in number as wages declined in real value.

In the early 1980s, another migrant type, which we call risk diversifiers, dominated the Mexico-to-US stream. These migrants came from households with substantial assets but were not household heads, and they lived in communities where the majority of households were self-employed. As interpreted by the new economics of migration theory, they migrated to the United States to secure earnings that insure against risks to household assets. These migrants reached high numbers when the Mexican inflation rate, a proxy for economic uncertainty, soared from the early to the late 1980s. As the inflation rate returned to normal in the 1990s, risk diversifiers also declined in numbers.

From the mid-1980s to early 1990s, network migrants became the majority among first-time Mexicans migrants to the United States. These migrants, mostly women with family or community ties to earlier migrants to the US, exemplified an interpretation of cumulative causation theory: past migration creates social ties to the destination, and these ties facilitate further migration. Network migrants remained constant in proportion, making up about one-fifth of all migrants, until the mid-1980s. In 1986, the Immigration and Reform and Control Act legalized 2.3 million undocumented migrants and increased the number of visas available to Mexicans. As a result, network migrants doubled in proportion and remained at that level until 2000.

Starting in the mid-1990s, a new migrant type quickly gained prevalence. This type, which we call urban migrants, was highly educated, worked mostly in manufacturing, and lived in metropolitan areas. Constituting the majority of migrants in the 1990s, urban migrants were not the subject of any individual-level theory. Yet, a general trend of increasing economic connectivity to the United States, and a resulting economic restructuring in Mexico, may explain the rise of this group in the MMP data. Given that urban migrants increased in proportion following the increased trade between Mexico and the United States after GATT and NAFTA, which also implied major structural changes in the Mexican economy, these hypotheses remain plausible but need to be evaluated in future work.

Revealing a well-defined pattern, each migrant type became dominant around the time in which its corresponding theory was developed. Income-maximizing migrants prevailed in the 1970s when Harris and Todaro (1970) published the defining article of the neoclassical economics perspective on migration. Risk diversifiers became the majority in mid-1980s when Stark and Bloom (1985) published the most influential article on the new economics of labor migration. Network migrants gained prevalence in the early 1990s when Massey (1990a) developed the cumulative causation theory of migration. This correspondence between migrants and migration theories suggests a relationship between empirical patterns and the scientific ideas that seek to explain them, and it calls for further study by sociologists of knowledge.

The empirical patterns identified in this study described the heterogeneity in the migration process across individuals and over time periods. The patterns suggest that different causal regimes may govern specific groups of individuals or specific periods. We scrutinized these causal regimes with regression analysis on sub-samples that included each migrant group and non-migrants. The results showed that a different set of factors mobilized each group, a variation that remained obscure in conventional regression analysis run on pooled samples. The results thus suggested cluster analysis as a potential solution to the sample-splitting or change-point problem in statistical analysis, concerned with identifying sub-samples for which the regression estimates are stable. A final set of analyses demonstrated that migrant groups vary not only in the reasons that mobilize them, but also in their experiences in the United States, a finding that confirmed the potential of the proposed typology for yielding testable hypotheses and extending existing theories.

The methodology applied here could be used to investigate any research question where there is heterogeneity in the causal mechanisms leading to a given outcome and where that heterogeneity can be characterized by identifying groups that vary with respect to key factors suggested in competing theoretical accounts. Recent studies have employed similar methods to categorize individuals into alternative theories of popular nationalism (Bonikowski 2012) and musical tastes (Goldberg 2011), or to group legislative voting behavior into rival theories of trade policy preferences (Imai and Tingley 2012).

Contributing to this line of research, the present application of cluster analysis allowed us to combine various theoretical perspectives on migration and to demonstrate the diversity of migrants. By searching for groups of individuals who share the same behavior but differ on configurations of characteristics, cluster analysis revealed the various mechanisms that apply to each group. This approach, although quantitative in method, is qualitative and historical in spirit. It is analogous to the case-oriented approach proposed by Ragin (1987), which seeks to identify "constellations, configurations and conjunctures" that define and distinguish each case. The approach is also similar to a "colligation" process, which involves piecing together various factors to explain a case, imported from history to sociology by Abbott (2001). The goal, similar to that of these authors, is to close the gap between theory and empirical evidence and between qualitative and quantitative methods in the social sciences.

Notes

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1 Most studies have focused on the social ties to migrants as the principal mechanism of cumulative causation. But research has also identified other factors, such as the regional distribution of human capital, the organization of agriculture, or culture, that might be affected by—and eventually affect—migration in a cumulative fashion (Massey et al. 1993). These factors are difficult to assess reliably with the survey data at hand and, thus, are not discussed at length here.

2 Detailed information on the MMP is available at «http://mmp.opr.princeton.edu/.»

3 Other related methods include latent class and growth curve models. The former focus on the variability in outcomes across unknown latent groups, and the latter identify the variability across trajectories. Neither is appropriate for our purpose, which is to group cases based on configurations of causal factors (not outcomes), while keeping the outcome constant.

4 In classical statistical estimation, converting continuous variables to binary attributes would lead to severe information loss. In cluster analysis, this approach is not only acceptable, but used often to "de-noise" high-variance variables (Legendre and Legendre 1983). More generally, because the goal in statistical estimation is to estimate or confirm a given quantity (e.g., a parameter), tuning data or methods to produce a result would lead to bias. By contrast, because the goal in cluster analysis is to create categories that reveal new information, tuning data or methods until we learn something useful is perfectly reasonable (Grimmer and King 2011).

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