# Discovering Diverse Mechanisms of Migration:

# The Mexico-U.S. Stream from 1970 to 2000*

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**Abstract**

Migrants to the United States are a diverse population. This diversity, captured in various migration theories, is overlooked in empirical applications that describe a typical narrative for an average migrant. Using the Mexican Migration Project data from about 17,000 first-time migrants between 1970 and 2000, this study employs cluster analysis to identify four types of migrants with distinct configurations of characteristics. Each migrant type corresponds to a specific theoretical account, and becomes prevalent in a specific period, depending on the economic, social and political conditions. Strikingly, each migrant type also becomes prevalent around the period in which its corresponding theory is developed.

> "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, p.13)

There are diverse mechanisms that lead individuals to migrate to the United States. These mechanisms are captured in various migration theories developed in multiple disciplines. In neo-classical economics, higher wages in destination propels migration of individuals who expect to earn more there (Harris and Todaro, 1970). In new economics of migration, uncertainty in the origin economy leads to migration from households that face risks to domestic earnings (Stark and Bloom, 1985). In cumulative causation theory, growing web of social ties between origin and destination fosters migration of individuals who are connected to prior migrants (Massey, 1990a).

In a seminal series of 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 those who join family or friends in destination. Massey and Espinosa (1997) provided the first empirical application of this argument in the Mexico-U.S. setting. Associating each theory to 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) vision, as 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 recent years, migration scholars have gained considerable ground in analyzing the causal heterogeneity of migration. Studies have employed restricted samples or interaction terms in a regression setting to show 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).

This study builds on this prior work, but provides a novel empirical strategy to identify the diverse mechanisms underlying migration. Rather than dissecting data based on fixed groups or trying various permutations of interaction terms in a regression model, we employ cluster analysis, an inductive and data-driven method, to discover the distinct causal configurations that characterize different migrant types.

Cluster analysis, originally derived in computer science, is a technique commonly applied in fields as diverse as biology and physics. This method allows us to characterize variation across cases, rather than selectively focusing on an average case as frequently done in quantitative social inquiry, typically within a regression framework (Abbott, 2001). Hence instead of asking "What factors determine who migrates?" we can now ask "Are there different types of migrants in different contexts? Are these types captured in different theories?"

This approach provides novel insights to understand the migration stream between Mexico and the United States, the largest contemporary flow in the world. The study period begins in 1970 and captures various important changes in the migration context until 2000: economic fluctuations in Mexico leading to more migration, U.S. migration policy shifting to prevent it, and still growing undocumented migration between the two countries. We use the Mexican Migration Project data from about 17,000 migrants on the year of their first migration to the United States. Our analysis applies the K-means clustering algorithm with various validation checks, and yields four distinct migrant types. Each migrant 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. Strikingly, each migrant type also becomes prevalent around the period in which the theory it corresponds to is developed.

## Background

### The Origins of Migration

Today 200 million people, roughly 3 percent of the world population, reside in a country other than the one they were born in (World Bank, 2009). 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 also led to a fragmented set of theories developed in multiple disciplines.

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; Todaro and Maruszko, 1987). The most likely migrants are individuals whose education and occupation permit higher earnings in destination compared to the origin. These predictions have received substantial empirical support. At the aggregate level, for example, researchers related Mexico-U.S. migration rates to wage and employment figures in both countries (Bean et al., 1990; Frisbie, 1975; Jenkins, 1977; White et al., 1990). At the individual level, researchers showed that the expected earnings in destination determined 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 act to tackle the 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 diversification strategy, where earnings in destination provide a hedge against shocks to domestic income (Stark, 1984; Stark and Levhari, 1982). As a result, migrants typically originate from households with substantial economic resources, a pattern observed in various settings including Mexico (Massey et al., 1987), 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). In the Mexican setting, for example, migrants' earnings are often invested in the origin community, which provides evidence to this theory (Durand et al., 1996; Lindstrom and Lauster, 2001; Massey and Parrado, 1994).

The neoclassical and new economics perspectives both 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 prior migrants in destination. Strong evidence confirms this expectation in Mexico (Davis and

Winters, 2001; Massey and Espinosa, 1997; Massey and Zenteno, 1999; Winters et al., 2001) and Thailand (Curran et al., 2005; Garip, 2008).

There are two other theories that 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 the native workers due to 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 as a response to the economic disruptions in their own countries and by capitalizing on their increasing cultural connections to developed regions due to globalization (Castells, 1989; Sassen 1988,1991).

**A Gap between Theory and Evidence**

This study focuses 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 in destination. New economics predicts risk-diversifying migrants who seek to complement earnings at risk in origin. Cumulative causation describes network migrants who follow family or friends in destination.

Each theory depicts a unique facet of the migration process, and combined together, they provide a more complete picture. Considering these complementarities, Massey et al. (1993, 1994, 1998) took on a massive 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-U.S. case, provided the first empirical application. The authors first 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 origin community signified the density of connections to prior migrants, an important factor leading to migration according to cumulative causation theory.

Using a regression model, and 41 such variables, the authors then evaluated which variables better predict who migrates in 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, creates a gap between theory and evidence on migration. First, the approach juxtaposes theories against one another as competing explanations of migration, not fully reflecting Massey et al.'s (1993) vision for these theories as complementary accounts. Second, the approach produces average results that are presumed to generalize to all individuals and across time. These results imply that migration theories, conditional statements in reality, apply universally within the scope conditions of the study. For example, in new economics theory, the uncertainty in the economy increases the migration probability of households facing risks to earnings or assets. In Massey and Espinosa's (1997) application, the uncertainty, measured by the Mexican inflation rate, increases the migration probability of everybody.

In recent years, migration scholars have made strides in addressing this issue of population heterogeneity, that is, the fact that different mechanisms may work for specific groups of cases. Gender 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 to the host society among migrants from different ethnic groups (Alba and Nee, 1997; Portes and Rumbaut, 1996; Portes and Zhou, 1993). Others have studied the varying causes of migration over time or across communities (Durand et al., 2001; Fussel and Massey, 2004; Marcelli and Cornelius, 2001; Massey et al., 1994). As an alternative to dividing samples based on gender, ethnicity, region or period, quantitative researchers have employed interaction terms in regression models to allow the effect of a factor to vary across groups, contexts, or time (Curran and Rivero-Fuentes, 2003; Garip and Curran, 2010; Lindstrom and Lauster, 2001).

**Bridging the Gap**

This study builds on these efforts, but proposes a novel approach to characterize the causal heterogeneity in migration. Rather than dissecting data based on fixed groups, or trying various permutations of interaction terms in a regression setting, this approach employs cluster analysis to discover the distinct causal configurations that characterize different migrant types.

This approach is inspired by Ragin and Abbott's work in sociology. According to Ragin (1987), there may be multiple causal bundles that lead to the same social or historical outcome, and these bundles may include various conditions that come together. To discover these causal bundles, which are both 'multiple' and 'conjunctural', Ragin developed boolean algebra and fuzzy set methods (Ragin et al., 1984; Ragin, 1994, 2000, 2008). Abbott (2001) similarly defined causes as specific configurations or sequences of events. To discover these configurations, he applied sequence analysis, a method commonly used in biology to classify DNA patterns, to social data (Abbott and Barman, 1997; Abbott and DeViney, 1992; Abbott and Hrycak, 1990).

Similar to these authors, our approach recognizes that different causal configurations may lead individuals to the same outcome, to migrate from Mexico to the United States. To discover these configurations, we employ cluster analysis, a data search technique for locating groups of cases with similar attributes. This approach, similar in spirit to Abbott's sequence analysis, is very different in its purpose. Sequence analysis is designed to discover typical sequences of a time-varying outcome, for example, migration histories of individuals. Cluster analysis, in this paper, is used to discover typical configurations of causal factors that define distinct types among migrants.[1]

Identifying configurations that characterize 'ideal' types has a long tradition in sociology (Weber, [1922] 1978). Today, this tradition survives mostly in qualitative studies. In quantitative work, "the statistical turn" in the last century has led to an exclusive focus on average cases identified through regression methods (Camic and Xie, 1994, p.773; Xie, 2007). Migration scholars, for example, have mostly focused on average differences between migrants and non-migrants, and neglected the variability within each group.

This study provides an empirical approach to fill this gap in the literature. First, we use cluster analysis to discover different types of migrants, and hence appropriate a quantitative method for a distinctly qualitative approach to social science. Second, we relate each type to a

[1] Other related methods include D'Unger et al.'s (1998) latent-class models built on the precursor models by Lazarsfeld and Henry (1968) and Goodman (1974), and Muthén and Muthén's (2000) growth curve models. The former focus on the variability in outcomes across unknown latent groups, the latter identify the variability across trajectories. Neither are appropriate for our purpose, which is to group cases based on configurations of causal factors (not outcomes), while keeping the outcome constant.

theoretical narrative, and offer an alternative way to link evidence to theory, where different narratives provide complementary, rather than competing accounts of migration. Third, we observe the temporal distribution of each migrant type, and identify when and for whom each theory is most relevant. This approach of identifying the surrounding circumstances for each finding resonates with the philosophy of small-N case studies. Hence, we combine insights from various approaches to social science research and various theories of international migration to discover the diverse mechanisms leading to the Mexico-U.S. flow.

## Migration from Mexico to the United States

### Major Milestones Since 1942

This study focuses on the migration from Mexico to the United States between 1970 and 2000. This flow, the largest in the world today, started in 1900s, but 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 end of the Bracero program marked a shift in the U.S. immigration policy. The 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 two peso devaluations in 1976 and 1982, set off 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 whom were undocumented (Massey et al., 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 (U.S. INS, 1990). As an unintended consequence, the amnesty created incentives for the relatives of the newly legalized Mexicans to also migrate (Massey and Espinosa, 1997). Undocumented migration to the United States continued as a result through the 1980s, considered the ‘lost decade’ for Mexico’s economy (Sheahan, 1991).

In 1994, two important events, the peso devaluation in Mexico and the North American Free Trade Agreement (NAFTA) between Mexico, United States and Canada, contributed to increasing migration flows to the United States. The former led to the worst economic crisis in Mexico in decades, and the latter displaced rural farmers through deregulation in agriculture (Fernandez-Kelly and Massey, 2007). As a result, from 1994 to 1998, U.S. border apprehensions rose from 1.1 to 1.7 million (Martin, 2003). By 2000, the 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-U.S. 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 on only 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 advantageous to study the diversity of the Mexico-U.S. stream. These data are not strictly representative of the Mexican population. Yet, prior work found that the MMP data yield an accurate profile of the U.S. migrants in Mexico, and this profile is largely consistent with that observed in the ENADID data (Durand et al., 2001; Zenteno and Massey, 1998).

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[2] The Mexican Migration Project is a collaborative research project based at the Princeton University and the University of Guadalajara. Detailed information is available on the project website. http://mmp.opr.princeton.edu/.

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 the U.S. migrants 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 timing of their first and last 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 with snowball sampling in the United States (about 10% of the sample).

Because more detailed information is available for household heads, most studies of the MMP have restricted attention to this sub-population. To provide a more representative portrait of migrants, this 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 as they are recorded only for household heads, and also to avoid a complication that has haunted prior work on migration. This complication arises from the fact that many attributes related to migration behavior are also changed by it. Over successive trips, migrants gradually gain more experience, establish stronger ties to destination, and become wealthier. Their attributes change, not as a result of the changing selectivity of the stream, but due to the changes caused by prior migration trips. Focusing on first-time migrants allows us to observe migrants' attributes independently from this reciprocal relationship.

There are two other concerns with the MMP data. First is the retrospective nature of the information on migrants. Let's take a household surveyed in 1990, where the daughter has migrated to the United States for the first time in 1980. Her attributes, like age and education, were recorded in 1990, but could be projected linearly to 1980. The economic status of her household could be reconstructed using the data on the timing of asset purchases. The characteristics of her community could be traced back using the retrospective community history. All 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.

Second, because each community was surveyed in a specific year, the sample contains migrants from a varying number of communities over time. The migrants come from 106 communities in the 1970s, 119 communities in the 1980s and 111 communities in the 1990s. This study restricts analysis to 17,049 first-time migrants observed from 1970 to 2000, when the majority of communities are represented consistently over time.

## 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 popularity of regression analysis.[3]

Regression analysis estimates parameters that characterize a relationship between an outcome and several attributes. These parameters capture causal effects if the researcher can credibly account for the unobserved heterogeneity in data. The causal effects, if expected constant over time, may lead to reliable outcome predictions. In most applications, however, regression estimates capture mere associations rather than causal relationships (Berk, 2004).

[3] Bailey (1975) provides a survey of cluster analysis for sociologists.

Cluster analysis produces a very different output. Rather than search for associations with an outcome, the method discovers groups in data based on the variability in several attributes. The results, although purely descriptive in essence, 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 into account these configurations by introducing interactions between attributes. But the number of possible interactions increases exponentially with the number of attributes and renders the model quickly unmanageable. Cluster analysis is a more efficient method for identifying the observed configurations of attributes. In fact, the method thrives on those configurations and is less useful in their absence.

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 data. This study seeks to discover distinct types of migrants based on various attributes in the MMP data. Qualitative studies suggest the presence of distinct groups among Mexico-U.S. migrants (e.g. Portes and Rumbaut, 2006), and quantitative analysis shows significant interactions among attributes in relation to migration behavior (e.g. 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.

## 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. This work, informed by migration theories, has identified several attributes that shape migration behavior (e.g. Massey and Espinosa, 1997). These attributes are used here to characterize the different migrant types.

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 (properties, land and businesses owned), prior migration experience (whether they migrated in Mexico, number of U.S. migrants and residents in 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).

[TABLE 1 ABOUT HERE]

The average values for these attributes differ significantly ($p<0,05$, two-tailed t-test) for migrants and non-migrants. Migrants are individuals who have migrated at least once and non-migrants are those who have never migrated. 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 U.S. 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 households with ties to U.S. 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 cluster analysis, are indicators that capture important economic or policy events, like the soaring Mexican inflation or interest rates in the 1980s or the passage of IRCA in 1986. These events introduce external shocks to the migration system, and typically shift the magnitude or composition of the migrant stream. Hence, they provide a perfect opportunity to evaluate 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., gender, occupation), a few are counts (e.g., number of properties 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, such 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 shown 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. This study employs the popular K-means method, a classical 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 former (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 latter (model-based) approach is advantageous if the data conform to a probabilistic model, and has proven useful in low-dimensional data sets. Yet, in our experience, the available software implementations of the model-based approach have poor performance with large and high-dimensional data sets like the MMP. For substantive and practical reasons, this study uses the K-means algorithm implemented in Matlab(R) software (Matlab, 2010, version 7.6). This algorithm, in addition to being generic

[4] In classical statistical estimation, converting continuous variables to binary attributes would lead to a 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, the goal in cluster analysis is to create categories that reveal new information, therefore tuning data or methods until we learn something useful is perfectly reasonable (Grimmer and King, 2010).

and fast, is in fact equivalent to the model-based approach for certain probabilistic models of the data.[5]

***Choosing a Similarity Measure*** Any clustering algorithm relies 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 specifying the algorithm itself (Hastie et al., 2009). Although there are no generic guidelines, researchers typically base their decisions on the nature of the data and the substance of the question.

For data with all binary attributes, as in our case, researchers have their pick from a multitude of similarity measures, but the question at hand typically imposes constraints. In some cases, researchers need to treat the similarity between two individuals who share a trait differently than two individuals who both lack it. In a simple example where individuals are endowed with a binary attribute that indicates whether they live in Chicago or not, two individuals living in Chicago would be considered more 'similar' than two others who both live outside of Chicago. The researcher, then, may use the Jaccard coefficient to assess similarity, which measures the proportion of positive matches between two individuals in all attributes. In other cases, a binary attribute exhausts all alternatives, such that its co-absence is as informative as its co-presence. In this study, for example, individuals are either male or female, have high or low education, and live in communities with high or low migration prevalence. Two individuals who both have high education are just as 'similar' as two others who both have low education.

[5] The K-means and model-based algorithms produce identical results if the data are described by a mixture of normal distributions and the covariance matrix of attributes is proportional to the identity matrix, and is the same for each cluster (Hastie et al., 2009). The K-means algorithm is typically very fast, but sometimes gets stuck at local minima, which may prevent the discovery of the optimal clustering solution in the data. To overcome this problem, the algorithm is run 1000 times in Matlab, each with a random initialization, and the solution with the minimum within-cluster variance is selected as the optimal solution.

The matching coefficient or city block measure aptly reflect this substantive preference. The former measures the proportion of all matches between two individuals in all attributes. The latter, a mere complement of the matching coefficient scaled by a constant, measures the sum of the absolute differences between two individuals in all attributes (Everitt, Landau, and Leese, 2001).

This study uses the city block distance to assess how close migrants are in various demographic, economic and social attributes. 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 $l=1,\ldots,p$,

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

Past work suggests choosing the simplest measure that satisfies the research goals to facilitate the interpretation of results (Sneath and Sokal, 1973). By using the city block distance, one of the most commonly-used and straightforward measures, this study follows this recommendation.

***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 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 hand panel, higher values indicate higher cluster quality. For the within-to-between distance ratio in the lower-right hand panel, lower values indicate higher cluster quality.[6]

[FIGURE 1 ABOUT HERE]

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. Specifically, the average distance in the left-hand panel, and the figure of merit in the right-hand panel, both evaluate whether the clustering solution remains stable if attributes are removed one at a time.[7] For both measures,

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[6] The Dunn Index is the ratio of the smallest distance between individuals in different clusters to the largest distance between individuals in the same cluster (Dunn, 1974). Hubert Gamma evaluates the congruence between two clustering partitions as a function of positive and negative agreements in pairwise cluster assignments (Hubert and Arabie, 1985). Goodman-Kruskal Gamma compares each within-cluster distance to each between-cluster distance. A pair of distances are concordant (discordant) if the within distance is smaller than (greater than) the between distance. The index equals the proportion of net concordant pairs (i.e., the total concordant minus discordant) in all pairs (Everitt et al., 2001). Within-to-between distance ratio is simply takes the ratio of the average intra-cluster distance to the average distance between clusters.

[7] The average distance computes the average distance between individuals who end up in the same cluster by clustering based on the full data and clustering based on the data with one attribute removed (Datta and Datta, 2003). The figure of merit measures the average variance in the removed attribute among individuals in the same cluster, when clustering is done with the remaining attributes (Yeung et al., 2001).

lower values indicate more stable clustering solutions. The 6-cluster solution yields the best score in both cases, but the 4-cluster solution is also a close contender, being located at a point where the slope of the curve changes dramatically.

[FIGURE 2 ABOUT HERE]

Based on these results, and 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 actually rare in clustering applications and increases our confidence in the validity of the results (Everitt et al., 2001; Milligan and Cooper, 1985).

***Assessing the Validity of Results*** Another useful way to assess the clustering results is to draw a cluster heat map. Used often in genetics to visualize gene expressions across samples, a heat map, in our context, shows the distribution of attributes across individuals in the four clusters. (See Wilkinson and Friendly (2009) for an introduction to heat maps.) Imagine 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 we stack the columns for all individuals side by side, while keeping the individuals in the same cluster together, we end 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 R. The rows show the attributes that are ordered so that the correlated attributes are close to one another. The columns represent the migrant individuals. The vertical black lines separate the four clusters.

[FIGURE 3 ABOUT HERE]

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 U.S. migrants. Those in cluster 4 are typically highly 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 U.S. migrants are typically located in communities with high levels of migration. Individuals with a high level of education are likely to be in urban communities. It is precisely due to these correlations that our data fall into distinct groups, providing a 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, which appear to be relatively uniform. 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 ($p< 0.05$, two-tailed test) from the value closest to it in all cases but one (U.S. migrants in the household). We interpret these values in light of migration theories and label each cluster as a specific migrant type.

[TABLE 2 ABOUT HERE]

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% of migrants in this group own a property, 11% own some land, and 5% own a business. About a third have migrated in Mexico. A small share has family ties to U.S. migrants (4%) or residents (4%). A larger share (34%), but still small compared to other clusters, live in communities with high migration prevalence. 80% of migrants in this group live in rural communities with high agricultural employment, and an equal share live in communities where a high proportion of individuals earn less than the minimum wage.

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

The second cluster consists of the wealthiest migrants in the sample. 76% of these migrants own a property, 38% own some land, and 16% own a business. Most of them have family ties to prior U.S. migrants (80%) and live in communities with high migration prevalence (60%). The majority are men (73%) and adult children (91%, *n.i.*), not heads, in the household. 40% (*n.i.*) of these migrants have primary education only, and about a third have some (24%) or complete (9%) secondary education. 85% 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 with 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 volatile economic climate of Mexico. 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 subsistence in Mexico. A risk diversifier is expected to migrate temporarily at times of high economic uncertainty. This expected pattern, which will be demonstrated in subsequent analysis, is probably facilitated by the migrant's ties to prior U.S. migrants in the family or community.

The third cluster is distinct in including mostly female migrants (62%) who are well-connected to other migrants. 81% have family ties to U.S. migrants, 17% are connected to U.S. residents, and 79% 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 a property, one in five owns some land, and only one in ten owns a business.

Compared to the first two clusters, a lower share of them (15%) live in poor communities, but a higher share (34%) are located in metropolitan areas.

A typical migrant in this group is the daughter of the household head who is unemployed. At least one member of her household, probably her father or husband, is a current or prior U.S. migrant. Given that she is not economically active, but connected to other migrants, we posit that this person migrates to join her family members in destination and label her as a 'network migrant.' Network migrants, those that 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 initiate 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 overwhelmingly live in urban metropolitan areas (81%). Most of them are male (80%) and twice as likely to be the adult children (60%) rather than the heads (31%) in their households. About one-third of these migrants have started, and about one-fifth have finished secondary education. 67% of migrants in this cluster own a property, and 14% own a business, the second highest share across all clusters. About a third of these migrants have family ties to U.S. migrants, and also a third live in communities with high migration prevalence. Only a small share of them live in communities with high agriculture (12%), or 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 who 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 a property, which provides him with economic security, but lacks risky assets like land or 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 migration theory, we call this person an 'urban migrant' to underline one of his most distinguishing and surprising characteristics.

The analysis so far discovered four migrant types in the Mexico-U.S. stream. While the first three types, labeled as income maximizers, risk diversifiers and network migrants respectively, corresponded to specific theoretical narratives, the final type, the urban stream, identified a new and unanticipated configuration. In the remainder of the paper, 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, first, justify the labels we have attached to the migrant types, and second, to expose 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 included migrants observed at different time points into a single cluster analysis and deliberately excluded indicators for economic or policy trends that capture the Mexico-U.S. migration context. Despite the exclusion of these trends, we still obtained results that show a strong temporal pattern.

[FIGURE 4 ABOUT HERE]

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 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 about only one-fifth of migrants in 2000. Network migrants, displayed in the lower-left panel, show constant presence through the 1970s and 1980s, including about 15% of all migrants. In the early 1990s, this group doubles in proportion and becomes a close second to the majority of urban migrants. Although accounting for about a fifth of migrants in earlier years, urban migrants 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 the urban migrants, the 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, as we 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 the 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 to 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 is rising consistently for both migrant groups over time, the difference between the two groups varies tightly around 1.2 years and remains significant ($p<0.05$, two-tailed test) in each period.

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

The changing prevalence of the four migrant types over time provides additional evidence to resolve a current debate in the migration literature. Comparing newer migrants to earlier ones, Marcelli and Cornelius (2001) found that the Mexican stream has become more diverse in gender and education composition, and more inclusive of migrants from urban and non-traditional geographic origins. On the other side of the debate, Durand et al. (2001) used a different sample to show that the Mexican stream has remained stable in gender, education or geographic characteristics over time. Our findings support the former result. They show that earlier cohorts of migrants on their first U.S. trip contain more income maximizers or risk diversifiers, who are likely to be men from rural areas with little education. Recent cohorts, by contrast, contain more network and urban migrants, and hence more women, more educated migrants, and more migrants from urban regions.

Our findings also reveal a cross-sectional variation in migrant characteristics that is largely neglected in the current debate. In each period, we observe four migrant groups with different configurations of attributes, albeit in changing proportions. In the 1970s, we observe mostly income maximizers, uneducated rural migrants, alongside a small number of highly educated urban migrants. Similarly, in the 1980s, we see a large number of risk diversifiers, most of whom are men with substantial assets, along with mostly female and unemployed network migrants. In the following section, we identify the contextual conditions that lead different migrants groups to assume the majority in different periods, and hence suggest potential sources of the temporal variation in migrant profiles.

**Bringing in the Context**

From 1970 to 2000, a number of economic and policy trends characterized the Mexico-U.S. migration context. We discuss these trends chronologically below, and consider their connection to the prevalence of different migrant types in our 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 in detail below.

Starting in the 1960s, Mexico experienced a prolonged decline in agricultural productivity (Heath, 1988; Martin, 2003). This decline led to a shortage of job opportunities (Roberts et al., 1999) and the worsening of living standards for low-income families in rural regions (Reyes-Heroles, 1983). Through the 1970s, the reductions in arable land and declining prices of agricultural products swept the country to a deep agricultural crisis (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). The workers that migrated to the United States filled farm jobs, which, following the Bracero program, had come to be defined as immigrant jobs and socially unacceptable to the U.S. citizens (Massey et al., 2003; Piore, 1979).

In our 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 the income maximizers, is 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 U.S. wages.

[FIGURE 5 ABOUT HERE]

The upper-left panel of Figure 5 displays the percentage of income maximizers alongside the average hourly U.S. wages over time. The values for the former series are shown in the left-hand-side y-axis, and the values for the latter (converted to U.S.$ in year 2000) are shown in the right-hand-side one. The two trend lines follow a similar path, and in fact are correlated at a remarkable +0.89. Income maximizers attain their largest share, comprising 40% of the sample, in 1970 when the U.S. wages are high, around 15$ per hour. The share of income maximizers recedes to 30% of in 1980, when the U.S. wages have declined to 13.5$ per hour, and eventually drops to 10% in 1990 when the U.S. wages obtain their lowest value of 12.5$ per hour. A similar pattern ensues if we juxtapose the percentage of income maximizers against the U.S.-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 rate of income maximizers and the U.S. wages not only confirms the label we have assigned to this group, but also suggests that neoclassical economics predictions hold in the Mexico-U.S. context for a specific group of individuals and under specific economic conditions. This observation reaffirms our initial claim that migration theories are conditional statements, and should be treated as such in empirical applications.

Along with the decline in agriculture, a number of conditions in the Mexican economy changed in the late 1970s. In 1976, after two decades of stability, the Mexican peso was devalued 45 percent in terms of the dollar. In the early 1980s, oil prices plummeted globally and caused a sharp decline in Mexico's revenues from oil exports. This decline, coinciding with two peso devaluations in 1982, led to a significant drop in wages, and sharp increase in inflation and interest rates (Meza, 2006). These conditions hit the Mexican middle class particularly hard (Escobar and Roberts, 1991). First, the 1982 crisis caused a shift in Mexico's development model, and led to the state's withdrawal from the agriculture sector and reduction of agricultural subsidies (Alba and Potter, 1986). As a result, middle-income rural families who owned small agricultural units faced serious setbacks. Middle-income urban families, similarly, experienced steeper wage declines than lower 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 originate from relatively wealthy households in rural communities. These migrants, called the risk diversifiers, experience the pronounced effect of the economic downturn and move to the United States to diversify the risks to their subsistence. If these migrants are indeed diversifying risks, as we assumed, 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 the trends in the percentage of risk diversifiers and 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 about half of the sample, in 1985 when the Mexican inflation rate is at its highest value of 60%. As the inflation rate drops to 10% in 1990, the share of risk diversifiers plunges to 25%. 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 marked a period of political backlash against undocumented migration in the United States which culminated in the passage of the Immigration Reform and Control Act (IRCA) in 1986 (Massey et al., 2003). IRCA, on the one hand, increased border enforcement and sanctions on 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 our sample, network migrants, mostly women joining their families in the United States, although present throughout the study period, proliferate in the years following IRCA. These migrants, mobilized by social ties rather than economic pressures as predicted by cumulative causation theory, become the second largest group in 1990, comprising about 30% of all migrants, a share they maintain 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 ratio of available visas to Mexican migrants. The two lines both spike in the same period immediately following IRCA. Although the ratio of visas drops after 1990, the network migrants retain their level due to higher incentives for the relatives of the 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 ratio of visas is only related to network migrants with documents, not to those who are undocumented.

The passage of IRCA in 1986, ironically, coincided with Mexico's admission into Generalized Agreement on Tariffs and Trade (GATT), which accelerated the trade flows between Mexico and the United States at an unprecedented rate. The implementation of the North American Free Trade Agreement (NAFTA) in 1994 further promoted the economic integration between the two countries. The maquiladora program for example, instituted in 1965 in the border Mexican states to provide cheap labor to U.S. firms, expanded from 600 plants employing 120,000 workers in 1980 to 4000 plants employing 1.3 million workers in 2000 (Durand et al., 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 international migrants to the United States (Zabin et al., 1993).

The Mexican economy, which appeared solid at the signing of NAFTA, experienced a severe 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% and its employment 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. Different than prior years, migrants in the post-NAFTA and post-crisis era included many educated professionals who were admitted for short-term labor. From 1994 to 1997, the number of Mexicans admitted for temporary work (under the H visa program) tripled and reached 37,000 persons per year (Durand et al., 2001).

In our sample, the majority of migrants in the 1990s are highly educated, work in manufacturing and live in urban areas. Labeled as the urban stream, these migrants are not anticipated in any migration theory, but could represent an extension of the globalization arguments, which predict increasing migration flows due to growing economic, cultural and ideological linkages between countries (Sassen, 1988, 1991, 1999). This line of thought predicts an increasing out-movement of individuals facilitated in part by the Westernization of advanced education systems (Portes and Walton, 1981) and work practices (Sassen, 1989) in developing countries. Extending this argument to the Mexican case, we can expect the educated individuals in urban areas to migrate in response to the increasing economic and cultural ties to the United States, especially after NAFTA, and given the dire economic conditions in Mexico at the time.[8] This hypothesis implies that the proportion of the urban stream should increase with increasing connectivity between Mexico and the United States, captured, for instance, by the trade flows.

The lower-right panel of Figure 5 compares the trends in the percentage of urban migrants and the logarithm of the Mexico-U.S. trade. The two series, correlated at +0.77, show

[8] The prevalence of educated migrants in the 1990s in our sample is consistent with evidence from other data sets. Using Mexican and U.S. census data, Chiquiar and Hanson (2005) showed that recent immigrants from Mexico are selected positively on education and wages. Studying all migrant groups in the United States, not just Mexicans, Jasso et al. (1998) also observed an increasing influx of educated migrants starting in the 1990s.

little movement until 1986, when both begin to move rapidly upward. Urban migrants become the largest group in 1990 and continually increase thereafter, mirroring the rapid uptake in the Mexico-U.S. trade. Although this pattern suggests the plausibility of the globalization hypothesis, more work is necessary to test it conclusively.

**Linking Empirical Patterns to Emergence of Theories**

The temporal patterns suggest that each migrant type, corresponding to a distinct theoretical narrative, gains prevalence under specific economic, social and political conditions. Income maximizers, representing the neoclassical narrative, are most prominent in the 1970s when the U.S. wages are at their highest. Risk diversifiers, personifying the new economic theory, gain majority in the 1980s when the Mexican inflation rate is at its peak. Network migrants, symbolizing the cumulative causation theory, obtain their highest proportion in 1990s when visa availability is at its highest.

[FIGURE 6 ABOUT HERE]

Revealing a striking pattern, the temporal order of the prevalence of the three migrant types coincides with the temporal order of the emergence of theories on which these migrant types are based. The three panels in Figure 6 show the proportion of income maximizers, risk diversifiers and network migrants, respectively. The vertical lines in each panel indicate the timing of the three most-cited articles in three theoretical perspectives: neoclassical economics, new economics of migration and cumulative causation. [9] (We do not include urban migrants in this analysis as this group does not bear a clear connection to any theoretical perspective,

[9] Citation data is obtained from the Social Science Citation Index (accessed in December 2009).

although appears related to general trends brought on by globalization. This link needs to be theorized, and verified empirically, in future work.)

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), when the income maximizers dominated the Mexico-U.S. migrant stream. Similarly, Stark and Levhari (1982), Stark and Bloom (1985) and Stark, Taylor and Yitzaki (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 announced the 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-U.S. flows.[10] This overlap suggests that different migration theories depict the dominant empirical trends around the period in which they were developed. Ironically, as these theories gain visibility and credence over time, their empirical value declines, at least in the Mexico-U.S. setting, because the conditions on which they are based no longer prevail.

## Conclusion

Sociology is a discipline with no dominant paradigm. Most questions can be approached from a variety of theoretical perspectives. But in empirical applications, this diversity often gets lost. To use prevailing quantitative methods, like regression analysis, researchers frame their questions around average differences, for example, between persons who display a behavior and those who do not, and reduce theories to competing sets of independent variables. If the corresponding variables capture statistically significant differences between groups, a theory is accepted;

[10] These authors were not the first ones to link migration to social networks. MacDonald and MacDonald (1964), Ritchey (1976), and Hugo (1981), to name a few, had previously argued that social ties to migrants facilitate migration. These articles, however, had less of an impact (in terms of citations) compared to the subsequent Massey and García-España (1987) and Massey (1990a, 1990b) publications.

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 an alternative strategy to capture the theoretical diversity in sociology. 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 captured 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 discovers 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 appears consistent with a specific theoretical account.

This approach provides a new perspective to understand the migrant stream between Mexico and the United States. This stream, the largest in the world today, continuously increased in the past decades leading to a migrant population of 8.4 million by 2000 (Bean et al., 2001). During this period, the economic, social and political conditions in the two countries changed drastically. These changes also shaped the character of the migrant stream, leading to a Mexican population that is diverse in backgrounds and objectives in the United States. This diversity, captured in a number of theories developed in economics and sociology, is overlooked in quantitative applications that focus on describing a typical narrative for an average migrant.

Applying cluster analysis to the Mexican Migration Project (MMP) data, from about 17,000 first-time migrants over a 30-year period from 1970 to 2000, this study identified four distinct types of migrants based on individual, household and origin community characteristics. These types corresponded to specific theoretical accounts and gained prevalence at specific time periods depending on the economic, social and political conditions in both countries.

Earlier 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 the U.S. wages were at their highest value in early 1970s, and slowly declined in number as the wages declined in real value.

In early 1980s, another migrant type, which we call risk-diversifiers, dominated the Mexico-U.S. stream. These migrants came from households with substantial assets, but were not household heads, and lived in communities where the majority of households were self-employed. As predicted 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 late 1980s. As the inflation rate returned back to normal in 1990s, risk-diversifiers also declined in numbers.

From the mid-1980s to early 1990s, network migrants became the majority among all first-time Mexicans migrants to the United States. These migrants, mostly women with family or community ties to prior U.S. migrants, exemplified a prediction of cumulative causation theory: past migration creates social ties to destination, which facilitate more 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 Act (IRCA) 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. These migrants, which we call the urban stream, were highly educated, worked mostly in manufacturing and lived in metropolitan areas. Constituting the majority of migrants in the 1990s, the urban stream was not predicted by any theory. Yet, a general trend related to globalization may apply specifically to this group: Increasing economic and cultural connectivity between countries fuels more migration. The educated individuals in urban areas of Mexico may be the first to respond to increasing economic ties to the United States. Given that the urban stream increased in proportion following the increased trade between Mexico and the United States after NAFTA in 1994, this hypothesis remains plausible, but needs to be seriously evaluated in future work.

Revealing a striking pattern, each migrant type became dominant around the time in which its corresponding theory was developed. Income-maximizing migrants prevailed in 1970s when Harris and Todaro (1970) published the defining article of the neoclassical economics perspective on migration. Risk-diversifiers become 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 unanticipated finding suggests a relationship between empirical patterns and the scientific ideas that try to capture them, and begs further study by the sociologists of knowledge.

The empirical patterns identified in this study show 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. These causal regimes could be scrutinized in future work with regression analysis on sub-samples that correspond to different groups or periods. For example, research could compare the factors that mobilize income maximizers to those that set in motion risk diversifiers. Similarly, studies could juxtapose the determinants of migration in the 1970-1982 period, when income maximizers prevailed, to those in the 1982-1986 period, when risk diversifiers gained majority. This approach, namely using descriptive observations based on cluster analysis to identify sub-samples, could provide a novel solution to the sample-splitting or change-point problem in statistical analysis, concerned with identifying time points between which the parameter estimates are stable.

This paper provided a strategy to combine various theoretical perspectives and to embrace the diversity of migrants. Rather than look for a causal mechanism that works for an average migrant, this approach recognized that there are different mechanisms that mobilize different migrant types under different conditions. For example, risk diversification is not always a reason for migrating, but becomes the major one for wealthy households during times of economic uncertainty. This perspective treated theories as conditional statements, rather than universal laws, and tried to determine for whom and under which conditions each theory works.

Cluster analysis allowed us to realize this vision. By searching for groups of individuals who shared the same behavior but differed 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 in solidarity with 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 these authors’, is to close the gap between theory and empirical evidence, and between qualitative and quantitative methods in the social sciences.

## References


Abbott, Andrew. 2001. *Time Matters: On Theory and Method.* Chicago: University of Chicago Press.

Abbott, Andrew and Emily Barman. 1997. "Sequence Comparison via Alignment and Gibbs Sampling: A Formal Analysis of the Emergence of the Modern Sociological Article." *Sociological Methods and Research* 27: 47-87.

Abbott, Andrew and Stanley DeViney. 1992. "The Welfare State as Transnational Event." *Social Science History* 16: 245-274.

Abbott, Andrew and Alexandra Hrycak. 1990. "Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians' Careers." *American Journal of Sociology* 96: 144-185.

Alba, Richard and Victor Nee. 1997. "Rethinking Assimilation Theory for a New Era of Immigration." *International Migration Review* 31: 826-874.

Alba, Francisco and Joseph E. Potter. 1986. "Population and Development in Mexico since 1940: An Interpretation." *Population and Development Review* 12(1): 47-75.

Arroyo, Jesus. 1989. *El abondono rural*. Guadalajara, Mexico: Editorial Universidad de Guadalajara.

Bailey, Kenneth. 1975. "Cluster Analysis." *Sociological Methodology* 6: 59-128.

Bean, Frank D., Rodolfo Corona, Rodolfo Tuiran, Karen A.Woodrow-Lafield, and Jennifer van Hook. 2001. "Circular, Invisible, and Ambiguous Migrants: Components of Difference in Estimates of the Number of Unauthorized Mexican Migrants in the United States." *Demography* 38: 411-422.

Bean, Frank D., Thomas J. Espenshade, Michael J. White, and Robert F. Dymowski. 1990. "Post-IRCA Changes in the Volume and Composition of Undocumented Migration to the United States: An Assessment Based on Apprehensions Data." In *Undocumented Migration to the United States: IRCA and the Experience of the 1980s*, edited by Frank D. Bean, Barry Edmonston, and Jeffrey S. Passel, pp. 111-158. Washington D.C.: The Urban Institute Press.

Berk, Richard A. 2004. *Regression Analysis: A Constructive Critique*. Thousand Oaks, CA: Sage Publications.

Brock, Guy, Vasyl Pihur, Susmita Datta, and Somnath Datta. 2008. "clValid: An R Package for Cluster Validation." *Journal of Statistical Software* 25: 1-22.

Camic, Charles and Yu Xie. 1994. "The Statistical Turn in American Social Science: Columbia University, 1890 to 1915." *American Sociological Review* 59: 773-805.

Castells, Manuel. 1989. *The Informational City: Information Technology, Economic Restructuring and the Urban-Regional Process*. Oxford, UK: Blackwell Publishers.

Cerrutti, Marcela and Douglas S. Massey. 2001. "On the Auspices of Female Migration From Mexico to the United States." *Demography* 38(2):187-200.

Chiquiar, Daniel and Gordon H. Hanson. 2005. "International Migration, Self-Selection, and the

Distribution of Wages: Evidence from Mexico and the United States." *Journal of Political Economy* 113(2): 239-281.

Cornelius, Wayne A. 1978. *Mexican Migration to the United States: Causes, Consequences, and U.S. Responses*. Cambridge, MA: Center for International Studies, Massachusetts Institute of Technology.

Curran, Sara R., Filiz Garip, Chang Chung, and Kanchana Tangchonlatip. 2005. "Gendered Migrant Social Capital: Evidence from Thailand." *Social Forces* 84: 225-255.

Curran, Sara R. and Estela Rivero-Fuentes. 2003. "Engendering Migrant Networks: The Case of Mexican Migration." *Demography* 40: 289-307.

Datta, Susmita and Somnath Datta. 2003. "Comparisons and Validation of Statistical Clustering Techniques for Microarray Gene Expression Data." *Bioinformatics* 19: 459-466.

Davis, Brenda and Paul Winters. 2001. "Gender, Networks and Mexico-U.S. Migration." *Journal of Development Studies* 38: 1-26.

Donato, Katherine M. 1993. "Current Trends and Patterns of Female Migration: Evidence from Mexico." *International Migration Review* 27: 748-771.

D'Unger, Amy V., Kenneth C. Land, Patricia McCall, and Daniel S. Nagin. 1998. "How Many Latent Classes of Delinquent/Criminal Careers? Results from Mixed Poisson Regression Analyses." *American Journal of Sociology* 103: 1593-1630.

Dunn, J.C. 1974. "Well-Separated Clusters and Optimal Fuzzy Partitions." *Cybernetics and Systems* 4: 95-104.

Durand, Jorge and Douglas S. Massey. 1992. "Mexican Migration to the United States: A Critical Review." *Latin American Research Review* 27: 3-42.

Durand, Jorge, Douglas S. Massey, and Rene M. Zenteno. 2001. "Mexican Immigration to the United States: Continuities and Changes." *Latin American Research Review* 36: 107-127.

Durand, Jorge, Emilio A. Parrado, and Douglas S. Massey. 1996. "Migradollars and Development: A Reconsideration of the Mexican Case." *International Migration Review* 30: 423-444.

Escobar, Augustin and Bryan Roberts. 1991. "Urban Stratification, the Middle Classes, and Economic Change in Mexico." In *Social Responses to Mexico's Economic Crisis of the 1980s*, edited by Mercedes Gonzalez de la Rocha and Agustin Escobar, pp. 91-113. San Diego, CA: Center for US-Mexican Studies.

Everitt, Brian S., Sabine Landau, and Morven Leese. 2001. *Cluster Analysis*. Arnold.

Fernandez-Kelly, Patricia and Douglas S. Massey. 2007. "Borders for Whom? The Role of NAFTA in Mexico-U.S. Migration." *The Annals of the American Academy of Political and Social Science* 610: 98-118.

Frisbie, Parker W. 1975. "Illegal Migration from Mexico to the United States: A Longitudinal Analysis." *International Migration Review* 9: 3-13.

Funkhouser, Edward. 1992. "Mass Emigration, Remittances and Economic Adjustment: The Case of El Salvador in the 1980s." In *Immigration and the Work Force: Economic*

*Consequences for the United States and Source Areas*, edited by George J. Borjas and Richard B. Freeman, pp. 135-177. Chicago: University of Chicago Press.

Fussell, Elizabeth and Douglas Massey. 2004. "The Limits to Cumulative Causation: International Migration from Mexican Urban Areas." *Demography* 41(1): 151-171.

Garip, Filiz. 2008. "Social Capital and Migration: How Do Similar Resources Lead to Divergent Outcomes?" *Demography* 45: 591-617.

Garip, Filiz and Sara Curran. 2010. "Increasing Migration, Diverging Communities: Changing Character of Migrant Streams in Rural Thailand." Forthcoming in *Population Research and Policy Review*.

Goodman, Leo A. 1974. "Exploratory Latent Structure Analysis Using Both Identifiable and Unidentifiable Models." *Biometrika* 61: 215-231.

Grasmuck, Sherri and Patricia R. Pessar. 1991. *Between Two Islands: Dominican International Migration*. Berkeley: University of California Press.

Hagan, Jacqueline M. 1998. "Social Networks, Gender, and Immigrant Incorporation: Resources and Constraints." *American Sociological Review* 63(1): 55-67.

Harris, John R. and Michael P. Todaro. 1970. "Migration, Unemployment and Development: A Two-Sector Analysis." *American Economic Review* 60: 126-142.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, second edition.

Heath, John. 1988. "An Overview of the Mexican Agricultural Crisis." In *The Mexican Economy*, edited by George Philip, pp. 129{163. London, UK: Routledge.

Hondagneu-Sotelo, Pierrette. 1994. *Gendered Transitions: Mexican Experiences of Immigration*. University of California Press.

Hubert, Lawrence and Phipps Arabie. 1985. "Comparing Partitions." *Journal of Classification* 2: 193-218.

Hugo, Graeme J. 1981. "Village-Community Ties, Village Norms and Ethnic and Social Networks: A Review of Evidence from the Third World." In *Migration Decision Making: Multidisciplinary Approaches to Microlevel Studies in Developed and Developing Countries*, edited by Gordon DeJong and R.W. Gardner, pp. 186-224. New York: Pergamon Press.

Jasso, Guillermina, Mark R. Rosenzweig and James P. Smith. 1998. "The Changing Skill of New Immigrants to the United States: Recent Trends and Their Determinants." *NBER Working Paper* 6764.

Jenkins, J. Craig. 1977. "Push/Pull in Recent Mexican Migration to the US." *International Migration Review* 11: 178-189.

Kanaiaupuni, Shawn Malia. 2000. "Reframing the Migration Question: An Analysis of Men, Women, and Gender in Mexico." *Social Forces* 78: 1311-1347.

Lazarsfeld, Paul F. and Neil W. Henry. 1968. *Latent Structure Analysis*. Boston, MA: Houghton Mifflin.

Legendre, Pierre and Louis Legendre. 1983. *Numerical Ecology*. Amsterdam: Elsevier.

Lieberson, Stanley and Freda B. Lynn. 2002. "Barking Up the Wrong Branch: Scientific Alternatives to the Current Model of Sociological Science." *Annual Review of Sociology* 28: 1-19.

Lindstrom, David P. and Nathaniel Lauster. 2001. "Local Economic Opportunity and the Competing Risks of Internal and U.S. migration in Zacatecas, Mexico." *International Migration Review* 35: 1232-1256.

MacDonald, John S. and Leatrice D. MacDonald. 1964. "Chain Migration, Ethnic Neighborhood Formation and Social Networks." *The Millbank Memorial Fund Quarterly* 42(1): 82-97.

Marcelli, Enrico A. and Wayne A. Cornelius. 2001. "The Changing Profile of Mexican Migrants to the United States: New Evidence from California and Mexico." *Latin American Research Review* 36: 105-131.

Martin, Philip. 2003. "Economic Integration and Migration." Discussion Paper No. 2003/35, World Institute for Development Economics Research.

Massey, Douglas S. 1990a. "Social Structure, Household Strategies, and the Cumulative Causation of Migration." *Population Index* 56: 3-26.

Massey, Douglas S. 1990b. "The Social and Economic Origins of Migration." *Annals of the American Academy of Political and Social Science* 510: 60-72.

Massey, Douglas S., Rafael Alarcon, Jorge Durand, and Humberto Gonzalez. 1987. *Return to Aztlan: The Social Process of International Migration from Western Mexico*. Berkeley and Los Angeles: University of California Press.

Massey, Douglas S., Joaquin Arango, Graeme Hugo, Ali Kouaouci, Adela Pellegrino, and J. Edward Taylor. 1993. "Theories of International Migration: A Review and Appraisal." *Population and Development Review* 19: 431-466.

Massey, Douglas S., Joaquin Arango, Graeme Hugo, Ali Kouaouci, Adela Pellegrino, and J. Edward Taylor. 1994. "An Evaluation of International Migration Theory: The North American Case." *Population and Development Review* 20: 699-751.

Massey, Douglas S., Joaquin Arango, Graeme Hugo, Ali Kouaouci, Adela Pellegrino, and J. Edward Taylor. 1998. *Worlds in Motion: Understanding International Migration at the End of the Millenium*. UK: Oxford University Press.

Massey, Douglas S., Jorge Durand, and Nolan J. Malone. 2003. *Beyond Smoke and Mirrors: Mexican Immigration in an Era of Economic Integration*. New York: Russell Sage Foundation Publications.

Massey, Douglas S. and Kristin Espinosa. 1997. "What's Driving Mexico-U.S. Migration? A Theoretical, Empirical, and Policy Analysis." *American Journal of Sociology* 102: 939-999.

Massey, Douglas S. and Felipe García-España. 1987. "The Social Process of International Migration." *Science* 237: 733-738.

Massey, Douglas S., Luin Goldring, and Jorge Durand. 1994. "Continuities in Transnational Migration: An Analysis of Nineteen Mexican Communities." *American Journal of Sociology* 99: 1492-1533.

Massey, Douglas S. and Emilio Parrado. 1994. “Migradollars: The Remittances and Savings of Mexican Migrants to the USA.” *Population Research and Policy Review*13: 3-30.

Massey, Douglas S. and Rene M. Zenteno. 1999. “The Dynamics of Mass Migration.” *Proceedings of the National Academy of Sciences* 96: 5328-5335.

Matlab. 2010. “Matlab 2010a: The Language of Technical Computing.” The Mathworks.

Meza, L. González. 2006. “Transformaciones económicas en México y migración a Estados Unidos.” In Migración México-Estados Unidos: implicaciones y retos para ambos paises, edited by A. E. Latapí E. Z. Herrera, J. A. Alejandre and G. V. Igartúa., pp. 173-193. México, D. F., Ediciones Casa Juan Pablos.

Milligan, Glenn W. and Martha C. Cooper. 1985. “An Examination of Procedures for Determining the Number of Clusters in a Data Set.” *Psychometrika* 50: 159-179.

Milligan, Glenn W. and Martha C. Cooper. 1988. “A Study of Standardization of Variables in Cluster Analysis.” *Journal of Classification* 5: 181-204.

Muthén, Bengt and Linda K. Muthén. 2000. “Integrating Person-Centered and Variable-Centered Analyses: Growth Mixture Modeling with Latent Trajectory Classes.” *Alcoholism: Clinical and Experimental Research* 24: 882-891.

Papail, Jean and Jesús Arroyo Alejandre. 2004. *Los dólares de la migración*. Guadalajara; Paris; Los Angeles: Universidad de Guadalajara; Institut de recherche pour le développement; Profmex; Casa Juan Pablos

Parrado, Emilio and Marcela Cerrutti. 2003. “Labor Migration between Developing Countries: The Case of Paraguay and Argentina.” *International Migration Review* 37: 101-132.

Pessar, Patricia R. 1999. “Engendering Migration Studies: The Case of New Immigrants in the United States.” *American Behavioral Scientist* 42: 577-600.

Piore, Michael J. 1979. *Birds of Passage*. Cambridge, UK: Cambridge University Press.

Portes, Alejandro and Ruben G. Rumbaut. 2006. *Immigrant America: A Portrait*. Berkeley and Los Angeles: University of California Press.

Portes, Alejandro and John Walton. 1981. *Labor, Class, and the International System*. New York: Academic Press.

Portes, Alejandro and Min Zhou. 1993. “The New Second Generation: Segmented Assimilation and Its Variants.” *Annals of the American Academy of Political and Social Science* 530: 74-96.

R Development Core Team. 2010. “R: A Language and Environment for Statistical Computing.” ISBN 3-900051-07-0, URL http://www.R-project.org.

Ragin, Charles C. 1987. *The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies*. Berkeley and Los Angeles, CA: University of California Press.

Ragin, Charles C. 1994. “A Qualitative Comparative Analysis of Pension Systems.” In *The Comparative Political Economy of the Welfare State*, edited by Thomas Janoski and Alexander M. Hicks, pp. 320-345. Cambridge, UK: Cambridge University Pres.

Ragin, Charles C. 2000. *Fuzzy-set Social Science*. Chicago: University of Chicago Press.

Ragin, Charles C. 2008. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago: University of Chicago Press.

Ragin, Charles C., Susan E. Mayer, and Kriss A. Drass. 1984. "Assessing Discrimination: A Boolean Approach." *American Sociological Review* 49: 221-234.

Reyes-Heroles, Jesus. 1983. *Politica macroeconomica y nienestar en Mexico*. Mexico: Fondo de Cultura Economica.

Ritchey, P. Neal. 1976. "Explanations of Migration." *Annual Review of Sociology* 2:363-404.

Roberts, Bryan R., Reanne Frank, and Fernando Lozano-Ascencio. 1999. "Transnational Migrant Communities and Mexican Migration to the U.S." *Ethnic and Racial Studies* 22: 238-266.

Root, Brenda D. and Gordon F. De Jong. 1991. "Family Migration in a Developing Country." *Population Studies* 45: 221-233.

Sassen, Saskia. 1988. *The Mobility of Labor and Capital*. Cambridge, UK: Cambridge University Press.

Sassen, Saskia. 1989. "America's Immigration 'Problem.'" *World Policy Journal* 6(4): 811-832.

Sassen, Saskia. 1991. *The Global City: New York, London, Tokyo*. Princeton, NJ: Princeton University Press.

Selby, Henry A. 1989. "The Effects of the Crisis in Mexico: The Case of Oaxaca." Texas Papers on Mexico, no.89-05, Mexican Center, University of Texas at Austin.

Sheahan, John. 1991. *Conflict and Change in Mexican Economic Strategy: Implications for Mexico and Latin America*. La Jolla: University of California at San Diego, Center for U.S.-Mexican Studies.

Sjaastad, Larry A. 1962. "The Costs and Returns of Human Migration." *Journal of Political Economy* 70S: 80-93.

Sneath, Peter H.A. and Robert R. Sokal. 1973. *Numerical Taxonomy*. Springer.

Stark, Oded. 1984. "Migration Decision Making: A Review Article." *Journal of Development Economics* 14: 251-259.

Stark, Oded and David E. Bloom. 1985. "The New Economics of Labor Migration." *American Economic Review* 75: 173-178.

Stark, Oded and David Levhari. 1982. "On Migration and Risk in LDCs." *Economic Development and Cultural Change* 31: 191-196.

Stark, Oded and J. Edward Taylor. 1989. "Relative Deprivation and International Migration." *Demography* 26: 1-14.

Stark, Oded and J. Edward Taylor. 1991. "Migration Incentives, Migration Types: The Role of Relative Deprivation." *The Economic Journal* 101: 1163-1178.

Stark, Oded, J. Edward Taylor and Shlomo Yitzhaki. 1986. "Remittances and Inequality." *The Economic Journal* 96: 722-740.

Stark, Oded and Shlomo Yitzhaki. 1988. "Labor Migration as a Response to Relative Deprivation." *Journal of Population Economics* 1: 57-70.

Taylor, J. Edward. 1986. “Differential Migration, Networks, Information and Risk.” *Research in Human Capital and Development* 4: 147-171.

Taylor, J. Edward. 1987. “Undocumented Mexico-U.S. Migration and the Returns to Households in Rural Mexico.” *American Journal of Agricultural Economics* 69: 626-638.

Todaro, Michael P. 1969. “A Model of Labor Migration and Urban Unemployment in Less-developed Countries.” *American Economic Review* 59: 138-148.

Todaro, Michael P. 1977. *Economic Development in the Third World*. New York: Longman.

Todaro, Michael P. and Lydia Maruszko. 1987. “Illegal Migration and U.S. Immigration Reform: A Conceptual Framework.” *Population and Development Review* 13: 101-114.

U.S. INS. 1990. *1989 Statistical Yearbook of the Immigration and Naturalization Service*. Washington, D.C.: U.S. Government Printing Office.

Wallerstein, Immanuel. 1974. *The Modern World System, Capitalist Agriculture and the Origins of the European World Economy in the Sixteenth Century*. New York: Academic Press.

Weber, Max. [1922] 1978. *Economy and Society: An Outline of Interpretive Sociology*. Berkeley, CA: University of California Press.

White, Michael J., Frank D. Bean, and Thomas J. Espenshade. 1990. “The US 1986 Immigration Reform and Control Act and Undocumented Migration to the United States.” *Population Research and Policy Review* 9: 93-116.

Wilkinson, Leland and Michael Friendly. 2009. “The History of the Cluster Heat Map.” *The American Statistician* 63: 179-184.

Winters, Paul, Alain De Janvry, and Elizabeth Sadoulet. 2001. “Family and Community Networks in Mexico-U.S. Migration.” *Journal of Human Resources* 36: 159-184.

World Bank. 2009. *World Development Report*. Published November 6, 2008, http://go.worldbank.org/K2CBHVB7H0.

Xie, Yu. 2007. “Otis Dudley Duncan’s Legacy: The Demographic Approach to Quantitative Reasoning in Social Science.” *Research in Social Stratification and Mobility* 25: 141-156.

Yates, P. Lamartine. 1981. *Mexico’s Agricultural Dilemma*. Tucson, AZ: University of Arizona Press.

Yeung, Ka Yee, David R. Haynor, and Walter L. Ruzzo. 2001. “Validating Clustering for Gene Expression Data.” *Bioinformatics* 17: 309-318.

Zabin, Carol, Michael Kearney, David Runsten, and Anna Garcia. 1993. “A New Cycle of Poverty: Mixtec Migrants in California Agriculture.” Davis, CA: The California Institute for Rural Studies.

## Figures

**Figure 1. Cluster Validation Measures Across Number of Clusters**

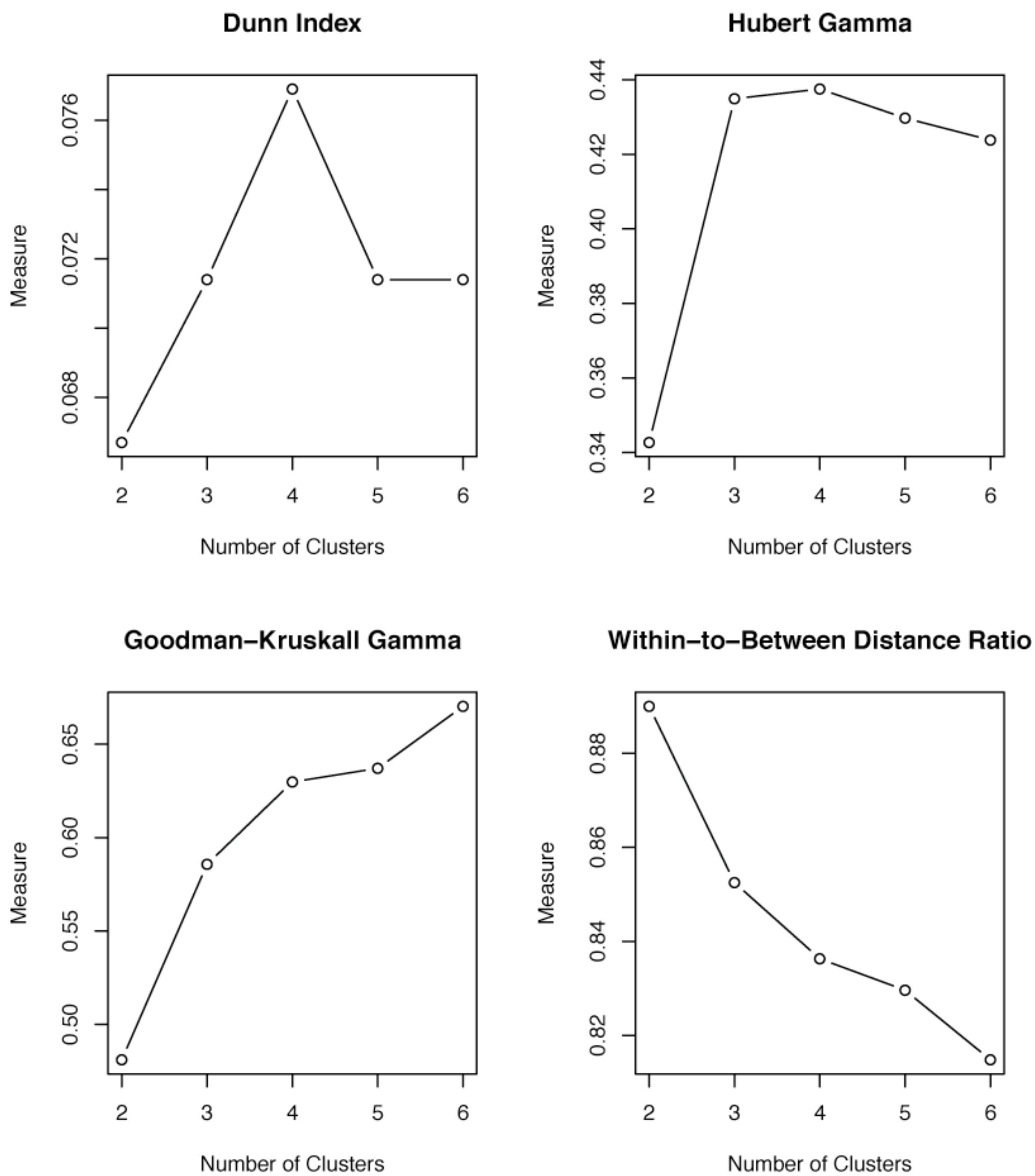


**Figure 2. Cluster Stability Measures Across Number of Clusters**

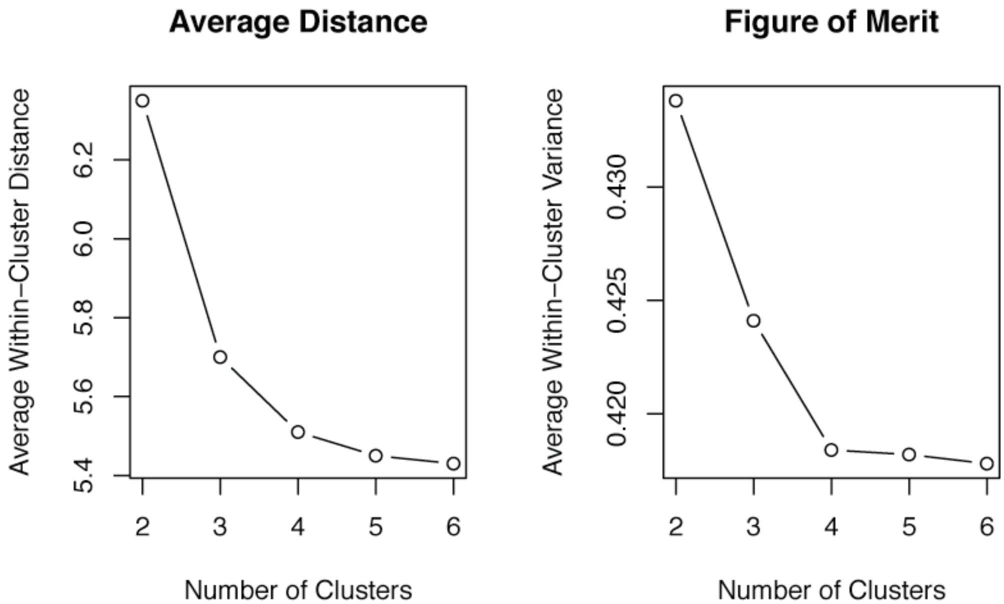
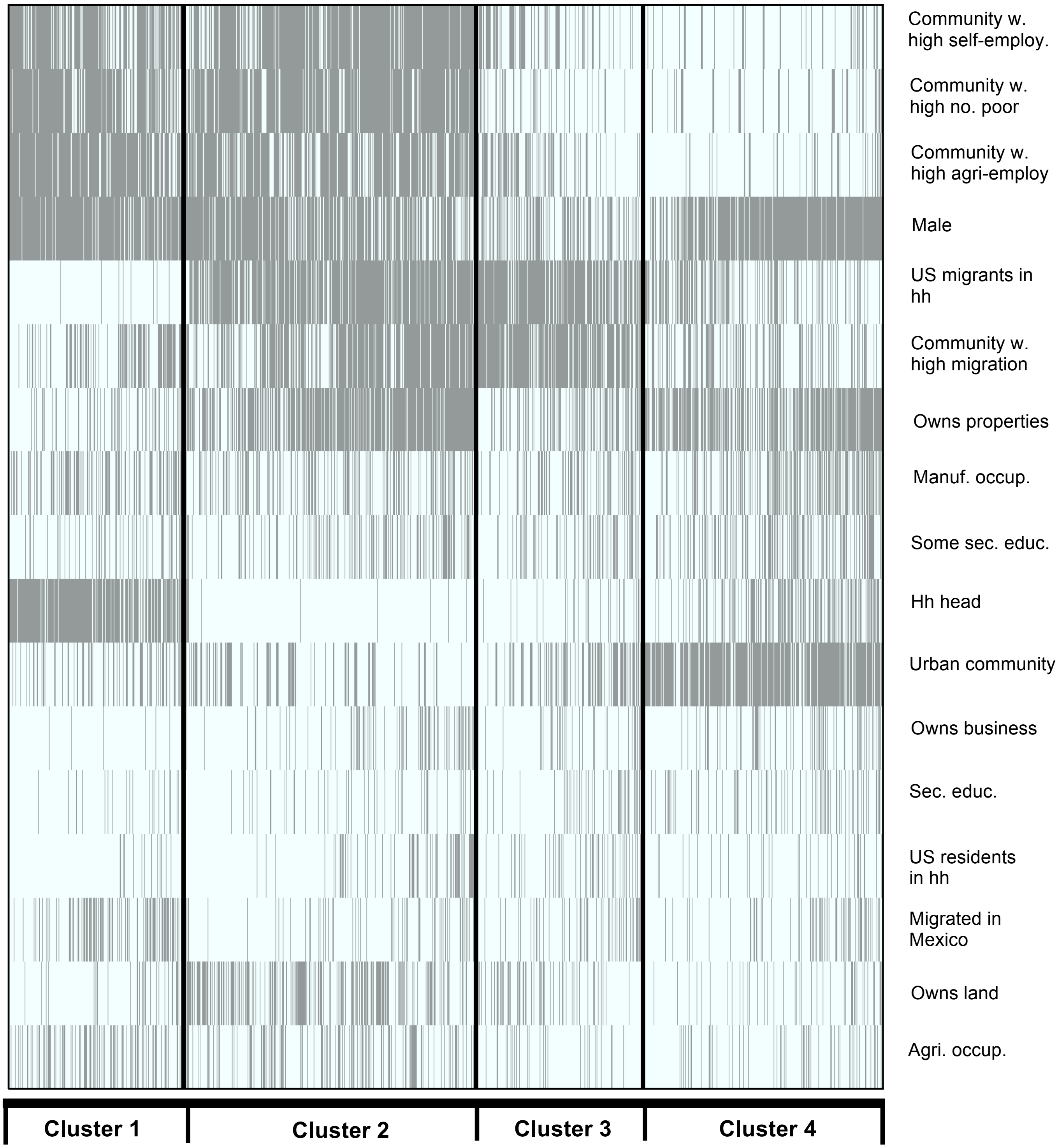


**Figure 3. Heat Map of Migrant Attributes by Cluster Membership**




*Note:* The heatmap color codes 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.

**Figure 4. Trends in the Distribution of Migrants Across Clusters**

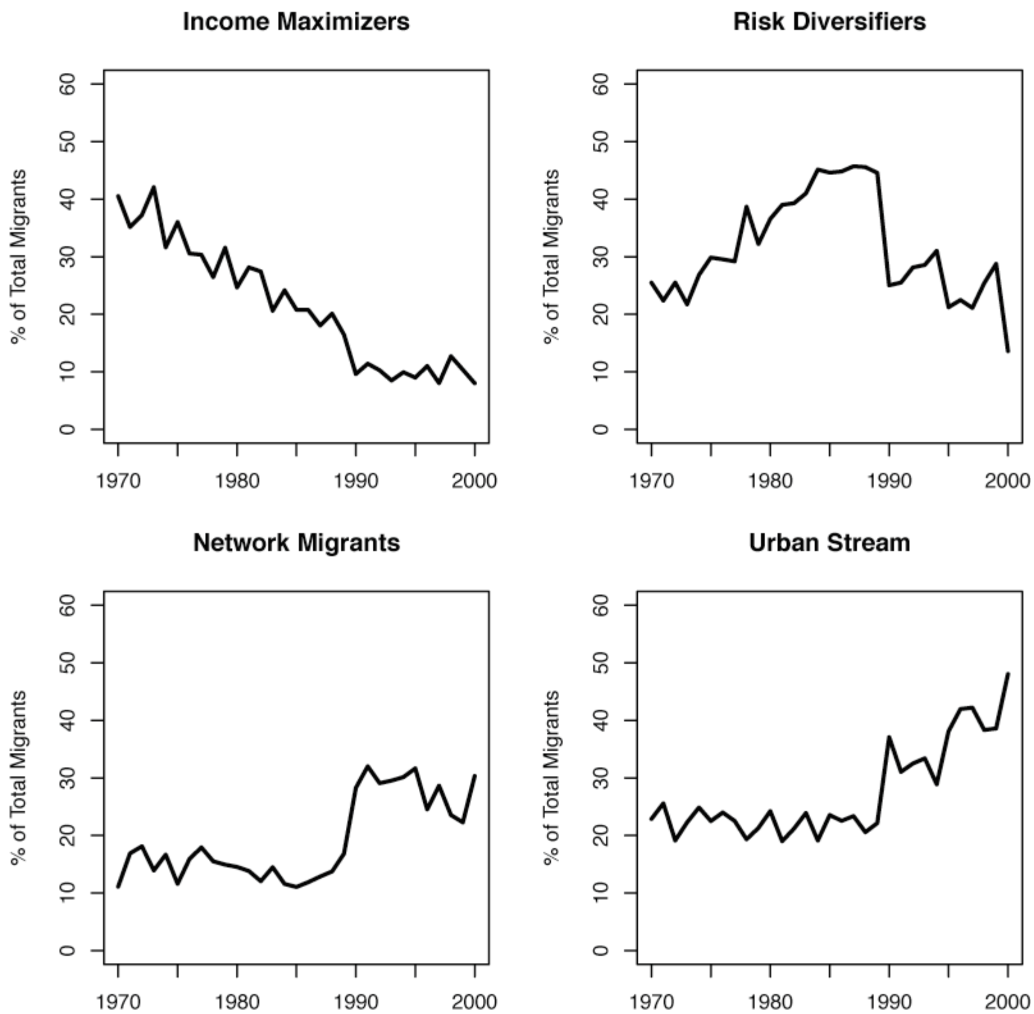


**Figure 5. Trends in the Economic and Political Context of Mexico-U.S. Migration**

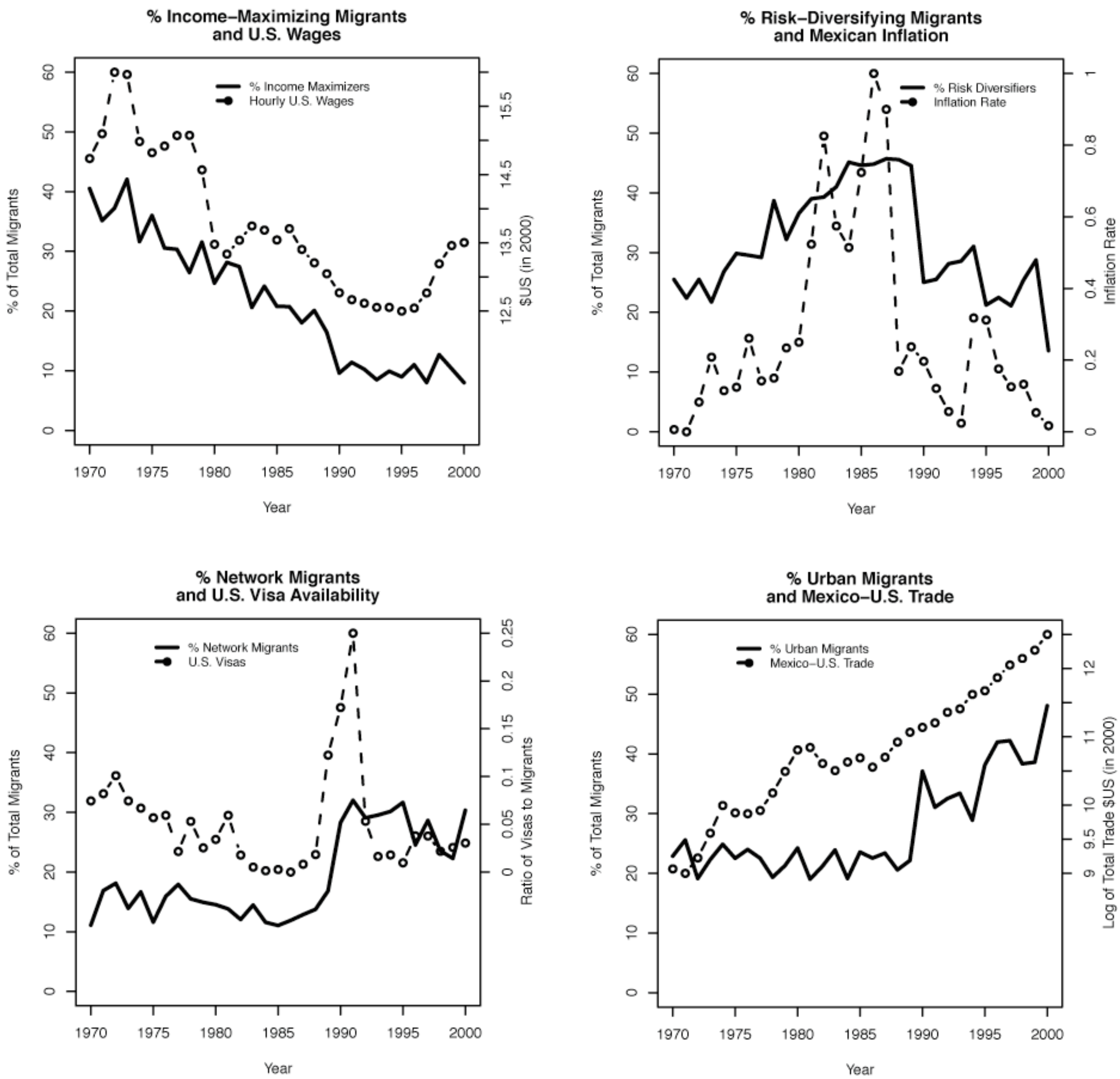
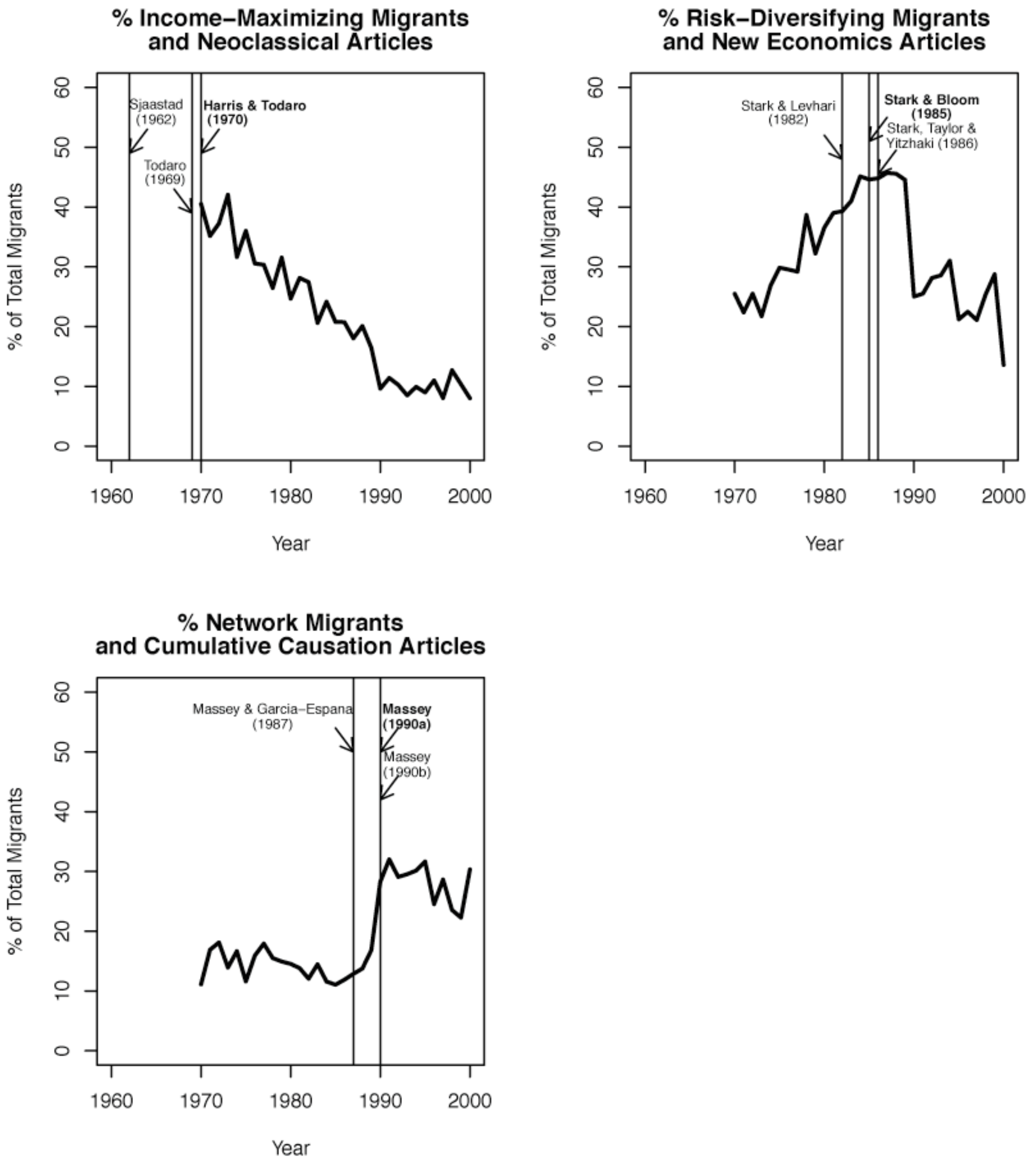


**Figure 6. Trends in the Distribution of Migrants Across Clusters and Emergence of Theories**




Note: Each figure shows the timing of the three most-cited articles for the corresponding theory. The top-cited article is in boldface. Citation data is from the Social Science Citation Index (accessed in December 2009).

# Tables

**Table 1. Sample Characteristics for Migrants and Non-migrants in 124 Mexican Communities[a]**

| Variable | Migrants | Non-migrants |
|---|---|---|
| Demographic characteristics | | |
| Household head | 0.28 | 0.12 |
| 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 |
| Household wealth | | |
| Number of rooms in properties | 4.21 | 3.61 |
| Log of land value (in US$ in 2000) | 3.12 | 2.15 |
| Number of businesses | 0.41 | 0.37 |
| Migration experience | | |
| Migrated in Mexico? | 0.22 | 0.17 |
| Number of U.S. legal residents in household | 0.48 | 0.13 |
| Number of U.S. migrants (non-residents) in household | 1.81 | 0.72 |
| Proportion ever migrated in community | 0.19 | 0.13 |
| Community characteristics | | |
| Proportion in agriculture in community | 0.28 | 0.24 |
| Proportion self-employed in community | 0.32 | 0.30 |
| Proportion earning less than min. wage in community | 0.38 | 0.34 |
| Community in metropolitan area | 0.41 | 0.50 |
| N (persons) | 17,049 | 107,838 |

a Migrants are individuals who have migrated at least once prior to 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.

**Table 2. Migrant Characteristics by Cluster Membership in 124 Mexican Communities** [a]

| 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** |
| Complete 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 | | | | |
| Own properties | 0.19 | **0.76** | 0.33 | 0.67 |
| Own land | 0.11 | **0.38** | 0.20 | 0.12 |
| Own business | 0.05 | **0.16** | 0.11 | 0.14 |
| Migration experience | | | | |
| Migrated in Mexico? | **0.33** | 0.12 | 0.14 | 0.18 |
| Any U.S. legal residents in household | 0.04 | 0.14 | **0.17** | 0.09 |
| Any U.S. migrants (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 | | | | |
| Community with high agriculture employment | **0.82** | 0.74 | 0.27 | 0.12 |
| Community with high self employment | 0.69 | **0.85** | 0.27 | 0.10 |
| Community with high no. of low earners | 0.79 | **0.83** | 0.15 | 0.13 |
| Community in metropolitan area | 0.26 | 0.20 | 0.34 | **0.81** |
| N (persons) | 3,522 | 5,569 | 3,271 | 4,687 |
| (% of total number of migrants) | 21 | 33 | 19 | 27 |

a The highest mean value for each variable is shown in boldface, and differs significantly from the value closest to it ($p<0.05$, two-tailed test) in all cases but one (any U.S. migrants in household).