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Testing Network Theory through an Analysis of Migration from Mexico to the United States

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Testing Network Theory through an Analysis of Migration from Mexico to the United States

by

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TABLE OF CONTENTS

<u>List of Tables and Figures</u>

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Abstract:

Very recently several writers in the study of international migration have recognized the role of social networks, or 'migrant networks', as an important force in explaining the perpetuity of international migration (Massey, 1987; Boyd, 1989; Massey et al., 1993, 1994; Portes, 1995). However this network effect has never been directly empirically examined. Traditional analysis using logit/logistic models makes unrealistic assumptions of the unmeasured common causes and, more often, does not control for relevant measured characteristics which may be correlated to the individuals in the network (Massey and Palloni, 1992).

In order to avoid these estimation problems a multi-state event history model, developed by Alberto Palloni and Douglas Massey, is employed using household level data from the Mexican Migration Project and the parameters of a Weibull function are estimated. This study specifically looks at the relationship between father and eldest son. For simplicity, the states are specified as unidirectional. State one is defined as both father and son reside in Mexico and have never migrated; state two is defined as when only the father has migrated to the United States; state three is defined as when only the eldest son has migrated to the United States; and state four is defined as when both father and son have migrated to the United States. A set of controls are added to the analysis, namely education, occupation and age, period effects, common conditions, as well as controls for unmeasured heterogeneity—which control for unmeasured 'common causes' between the pairs under examination. Predicted probabilities are then compared and contrasted and life tables are created.

When examining the migration experience between father-son pairs, the effects of social networks maintain as the most significant force in affecting the risk of migrating after controlling for selection and common causes, both measured and unmeasured. In particular, the probability of migrating is higher for those fathers whose son had migrated first (transition $3\rightarrow4$) compared to households where the father migrated first (transition $1\rightarrow2$). The hazard is also higher for those sons whose father had migrated first (transition $2\rightarrow4$) compared to those where the son migrated first (transition $1\rightarrow3$), net of individual effects and community characteristics.

Introduction

There are several schools of thought that aim to explain why people migrate. Varying from the macro level of analysis, such as those provided by 'push pull' theories, to the micro level of analysis, i.e., 'rational choice' theory, the migration literature spans many different fields which employ differing assumptions and hypotheses for why people move. The most contemporary treatment of the theoretical positions in the literature comes from Massey and his colleagues (Massey et al., 1993, 1994). The latest emphasis in the demographic and sociological literature however, has focused on what has been coined 'social network theory' (Massey and Espana, 1987; Boyd, 1989; Durand and Massey, 1992; Massey et al., 1993, 1994). Although it has evolved into a set of clearly defined propositions and has been given a place in the migration literature (Boyd, 1989; Massey et al., 1994; Portes, 1995), the contention of this paper is that it has not been adequately verified. This study attempts to advance our knowledge of migrant networks by examining and employing a multi-state event history model which allows the researcher to control for both common causes and selectivity effects (Massey and Palloni, 1992).

Defining of Social Networks

Migrant networks are defined in the extant literature as recurrent sets of interpersonal ties that bind migrants and non-migrants together within a web of reciprocal obligations that can be drawn upon to facilitate entry, adjustment, and employment at points of destination (Massey, 1987; Boyd, 1989; Portes, 1995). A social connection to someone with migrant experience at a particular destination represents an important resource that can be utilized to facilitate movement. Movement of one person within a network transforms the relationship into a valuable connection that can be used by anybody within the network to facilitate migration. Boyd (1989) argues that the recognition of social relationships and its role in international migration adds an important theoretical emphasis, refocusing the act of migration away from either the ‘oversocialized’ deterministic view of social structure[1] or the ‘undersocialized’ perspective of atomized rational actors. This middle perspective, which highlights the social forces involved in the migration, refocuses the analysis of international movement: “Thus, studying networks, particularly those linked to family and households, permits understanding migration as a social product—not as the sole result of individual decisions made by individual actors, not as the sole result of economic or political parameters, but rather as an outcome of all these factors in interaction” (Boyd, 1989, pg. 642).

One implication of this thesis is that the process of being socially connected to someone who has migrated necessarily creates a migratory information feedback mechanism, where contacts act as conduits of information to potential migrants.[2] As phrased by Portes, “Migration is defined as a network-creating process because it develops an increasingly dense web of contacts between places of origin and destination. Once established such networks allow the migration process to become self-sustaining and impervious to short-term changes in economic incentives” (Portes, 1995, pg. 22).

There are several conceptual models that can be employed to explain how social networks operate. The first is the social capital model, which assumes that actors migrate to maximize returns on their investments in human capital and, in doing so, draw upon the social capital embedded in their interpersonal networks. Portes defines social capital as:

[1] For example, World Systems and Labor Market Theory; for a detailed analysis of both these theories the

> "… the capacity of individuals to command scarce resources by virtue of their membership in networks or broader social structures. Such resources may include economic tangibles like price discounts and interest-free loans, or intangibles like information about business conditions, employment tips, and generalized 'goodwill' in market transactions. The resources themselves are not social capital; the concept refers instead to the individuals' ability to mobilize them on demand. The key conceptual characteristic of such resources is that, from a market standpoint, they are free to recipients. They have the character of 'gifts' since they are not expected to be repaid by a certain amount of money or other valuables in a given period of time" (Portes, 1995, pg. 12).

With the use of social capital the costs and risks associated with the act of migrating are reduced, i.e., access to safe transportation, housing, employment, and social interaction, and thus the probability of migrating is increased.[3] Similar to some economic models of migration, the social capital theorists assume that individuals will instrumentally use their networks as a means of gaining the highest returns on their investments in human capital. Additionally, social capital theory assumes that access to social connections, in the form of migrant networks, reduces the cost of movement and favors the act of migration to places where there exists a social tie (Massey and Palloni, 1992).

The second model is the risk diversification model, which posits that households are the decision-making units. This model draws its inspiration from what has been called the "new economics of migration"—which argues that determinants and the decision making process of international migration must be studied at the household level, not the individual level (Stark and Levhari, 1982; Stark, 1984a; Stark and Bloom, 1985; Katz and Stark, 1986). From this orientation one can extract two separate hypotheses: the decision to migrate may be to maximize expected income of the household (which gives rise to what has been observed as 'chain migration'), but it may also be to minimize the risk and loosen the constraints

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reader can turn to Massey et al. 1993 and 1994.
[2] This line of argumentation is credited to Alberto Palloni.

associated with market failures.[4] The second hypothesis posits that households utilize their networks in order to diversify their household income. By sending a member of the household abroad to another financial market, the household can effectively distribute its financial risk. Subsequently the first member who is sent abroad can be a contact so if the condition arises, such as a market failure, the household can send other members to that same location by taking advantage of the bridge made by the first mover (Massey and Palloni, 1992).

However, there are two counter-theses which potentially threaten what has been observed as a 'network effect': 1) 'Common Cause' hypothesis, which states that the high association of migration of people who belong to a network really owe the effect to larger social forces that influence everyone in the network to migrate. Individuals within a network may be influenced by measured/unmeasured common factors, making the effect of the network a spurious relationship owing to the common causes. 2) 'Self Selection' hypothesis, which posits that there may be some kind of non random selectivity effect which explains why networks seem to matter, but really are part of a self-selection process; that is, the selection factors that determine network membership may be simultaneously related to the propensity to migrate.

Empirical tests have confirmed that coming from a community which has a high rate of migration, or knowing someone who has migrated, is associated with migrating across international lines (Massey and Espana, 1987, Massey et al., 1993, 1994). Using logits or

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[3] The various conceptual models which explain how networks may operate at the household level are more elaborately detailed in Massey and Palloni's working paper (1992) "Studying Network Migration with Multistate Hazards Models."

[4] If the household is trying to maximize its total income, then the use of networks may only be a sufficient cause of migration, whereas wage differentials would be necessary.

logistic regression models on aggregate statistics, it has been shown that individuals related to someone with migrant experience are far more likely to migrate than individuals without that relationship. In addition, households that have relatives living in destination areas, or that have members with experience in those areas, are more likely to send migrants than those who do not (Massey, 1987; Massey and Espana, 1987).

However, the majority of these empirical studies have not been able to rule out the common cause hypothesis or the selectivity hypothesis. Only through a relaxed interpretation of the coefficients is the network effect posited. As lamented by Massey on the state of immigration studies in general: "Among the empirical studies that purport to be analytic, furthermore, a lamentably large proportion are flawed. The statistical methods they employ are rudimentary or biased, the models are simplistic, and appropriate controls are lacking" (Massey et al., 1994, pg. 700).

Specifically in linear models, which predict an outcome of migration, the conventional assumptions of the error term may not hold. But more commonly, by examining aggregate statistics, these studies cannot rule out the self-selection hypothesis. This study readdresses the proposed network hypothesis by analyzing the specific relationship between family members in terms of their relative propensity to migrate—specifically between fathers and their eldest son. By narrowing the focus to these pairs within a household, I am able to rule out the self-selection hypothesis because one usually cannot select themselves into a family. Although this paper does not directly adjudicate between which of the theoretical models explains why people use networks, it adds to the migration literature by utilizing a multi-state event history model developed by Palloni and Massey which allows for the falsification of the social network effect (Massey and Palloni, 1992). But before looking at the model and findings, I briefly review the possible models that could be used to examine migrant networks.[5]

Models and Tests of H_o

This section of the paper discusses four statistical models that can be used to estimate network effects: logit/probits, first differences, tobits, and bivariate hazards. This line of argumentation assumes that the researcher looks at specific pairs of people within a given network, in this example between father and eldest son, and secondly that the data are randomly sampled from the point of origin. The first criteria effectively rules out the selection hypothesis, which most research using aggregate data fail to control for, while the second criteria addresses bias.

After working through some of the problems and benefits offered by various models, this section concludes that the best means to control for both measured and unmeasured common causes while also examining the effects of social networks is best estimated with a multi-state hazard model.[6]

One way a researcher may examine migration might be to employ a logit/probit model. Examining the likelihood of migration as a probability or a linear function of the log-odds/logit, one could construct a dichotomous variable $Y_{1j}(t)$, representing individual *1* within

[5] A more comprehensive review of models for couple level data are reviewed and examined in Rob Mare and Alberto Palloni's paper "Couple Models for Socioeconomic Effects on the Mortality of Older Persons" (CDE Working Paper 88-7.)

[6] The following summary regarding model selection employs the work from Massey and Palloni's 1992 working paper "Studying Network Migration with Multistate Hazard Models."

social context *j* at time *t*. The dependent variable is the log odds of the event occurring, for example coded 1 if migration has occurred by time *t* and 0 otherwise. According to network theory, individuals who are related to one another in social context *j* are expected to influence one another's behavior. So if one person in *j* migrates, the risks of migration are hypothesized to increase for the other members in social context *j* as well. Thus if we were interested in examining the association between fathers and sons, we could express the following model:

(eq 1) $$Y_{1j}(t) = \alpha_{1j}X_{1j} + \alpha_{2j}X_{2j} + \beta_j Z_j + \varepsilon_{12j}$$

where X_{1j} is a vector of characteristics for individual *1* (Father's characteristics for example), X_{2j} is a vector of characteristics for the son *2*, in this example, and Z_j is a vector of characteristics associated with the household *j*; a_{1j}, a_{2j} and b_j are vectors of effects, and e_{12j} is the error term which has a mean of zero and is normally distributed. Z_j can, in fact, be parsed into three separate subvectors: Z_j' which represents the common causes that affect the migration risk of individual *1*, while Z_j'' represents the effect of the household characteristics on the other members of the household such as the son *2*, and Z_j''' is the effect on other members in the household not in the equation (Massey and Palloni, 1992).

The problem with this kind of model is that it is difficult to avoid statistical collinearity. In fact by its specification one would expect a perfect relationship between Z_j and X_{1j} and X_{2j}. However the most problematic feature of this model is not what it measures, per se, but its inability to parsimoniously control for unmeasured causes. It is possible that there are unmeasured characteristics, which are correlated with both individuals in the network, but are not included in the survey (Massey and Palloni, 1992).

So in light of the facts presented above the researcher can turn to a second model, a model of first differences (Massey and Palloni, 1992). As in a fixed effects model, the outcome is a function of differences between individual characteristics associated with each member of the pair. Therefore, $Y'_1(t)$ equals 1 if the father in the household *j* migrated before the eldest son and 0 otherwise:

(eq 2) $$Y'_1(t) = \alpha' X'_j + \varepsilon'_j$$

But in this case, the independent variables are the differences between the two people who are under investigation; namely, X'_j is a vector of differences between the characteristics of father and eldest son within household *j*; *a'* is a vector of effects associated with the effect of individual differences; and e'_j is the error term which is normally distributed with a mean of 0. The effects of unmeasured variables at the household level will not contaminate the estimates obtained from this model because the common conditions cancel out in the subtraction (Massey and Palloni, 1992). However the one issue with this model is that the reciprocal influence exerted by the individuals in the pair cannot be modeled directly. Furthermore, in the analysis of data from the point of origin, this model by itself is limited in its inability to account for censored cases.

The third kind of model, the tobit, presents an alternative to the models presented above by allowing for the inclusion of censored information. Its formal representation can be expressed as:

(eq 3) $$Y_{1j} = \beta_{1j} X_{1j} + \varepsilon_{1j}$$

(eq 4) $$Y_{2j} = \beta_{2j} X_{2j} + \varepsilon_{2j}$$

Y represents the interval of time until migration, from some specified time origin, or else receives a value of 0 if the case is censored.

As with most models that estimate survival time, the tobit assumes that censoring depends on the same variables and parameters as survival (Mare and Palloni, 1988).[7] The reason why this model is less preferred, for the concern of this paper, is because although it can account for censored cases it still lacks in its ability to capture the network effect parsimoniously.

The fourth alternative, the bivariate hazards model, preserves the advantages of both the first differences model and the tobit model. The dependent measure is the risk of the event occurring, or hazard. In this case the researcher can imagine estimating two equations: one for the father and one for the son.

(eq 5) $$\mu_j(t_1) = \exp(\alpha_{1j}X_{1j} + \beta_j Z_j + \theta W_j + \varepsilon_{1j})$$

(eq 6) $$\mu_{2j}(t_2) = \exp(\alpha_{2j}X_{2j} + \beta_j Z_j + \theta W_j + \varepsilon_{2j})$$

where *m* represents the hazard of migration, X_{ij} (i=1 for fathers and i=2 for sons) refers to the measured characteristics of person i in household j, Z_j indicates measured common characteristics of household j, W_j indicates unmeasured household characteristics, and ε represents unmeasured individual level characteristics.

To estimate this model, a duration structure for the hazard (Weibull, Exponential, Gompertz) must be estimated. However the bivariate hazards model has one major shortcoming: It is theoretically estimable only in the absence of reciprocal influences. Namely, it assumes that the association between the father's and son's survival time to migration is due entirely to the individual and common traits and not to the influence of one on the other. Thus the effect of migration by one household member on the migration risks of another is contained in the residual (Mare and Palloni, 1988; Massey and Palloni, 1992).

A Flexible Multi-state Model

To resolve the modeling problems mentioned above one could turn to the multi-state bivariate hazards model, or a competing risk model. In the case of father-son migration, we can imagine four distinct states with respect to the household timing of migration: neither the father nor the son has migrated, the father migrates but not the son, the son migrates, but not the father, and both the father and son have migrated. The hazards associated with the flows out of and into the four states can be represented either parametrically or non-parametrically so we can simultaneously estimate:

(eq 7) $$\mu_{12}(t_k) = \exp(\alpha X_{1j} + \beta Z_j + \theta W_j + \varepsilon_{12})$$

(eq 8) $$\mu_{13}(t_k) = \exp(\alpha X_{2j} + \beta Z_j + \theta W_j + \varepsilon_{13})$$

(eq 9) $$\mu_{24}(t_k) = \exp(\alpha X_{2j} + \beta Z_j + \theta W_j + \varepsilon_{24})$$

(eq 10) $$\mu_{34}(t_k) = \exp(\alpha X_{1j} + \beta Z_j + \theta W_j + \varepsilon_{34})$$

where the four hazards *(m)* represent risks of making the transition to four different event states for the household. X_1 refers to the vector of measured characteristics for the father in household *j*, while X_2 is the vector of measured characteristics for the son in household *j*. Z_j indicates measured common characteristics of household *j*, and W_j indicates unmeasured household characteristics.

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[7] For a more thorough analysis of the Tobit model, the reader is encouraged to turn to J. Scott Long's "Regression Models for Categorical and Limited Dependent Variables."

Similar to the bivariate hazards model, the researcher must specify a functional form of the hazard. However, the most important advancement this model has over the other models is that we can now examine the effects between hazards while controlling for both measured and unmeasured common causes.[8]

The primary limitation with using this kind of model pertains to available data. Until recently most studies examined migrants at points of destination, which may have selectivity issues. But for this multi-state event history model the researcher needs to utilize a data set that not only samples from the point of origin but also contains a sufficient number of cases with detailed migration histories.

Data

The data for this study come from the Mexican Migration Project, funded by the National Institute of Child Health and Human Development, which contains information from thirty-nine Mexican migrant sending communities. The communities were chosen to provide a range of different sizes, regions, ethnic compositions, and economic bases. The communities surveyed come from seven of the thirty-one states in Mexico which are located on the western central coastline. The sample includes isolated rural towns, large farming communities, small cities, and very large metropolitan areas. The final dataset of 3,036 father-son pairs is well distributed across the different types of community: metropolitan, 833, 28%; small urban, 822, 27%; town, 703, 23%; and ranch, 678, 22%. The towns vary in their ethnic composition as well as their occupations (Massey, Goldring, and Durand, 1994).

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[8] The method used to control for unmeasured heterogeneity involves the techniques developed by Heckman and Singer.

Two to five Mexican communities were surveyed each year, beginning in 1982, using simple random sampling methods. Sample size was 200 households in communities with more than 500 residents, otherwise it was smaller. The Mexican community surveys provided information on migrant destinations within the United States. Non random interviews were then conducted in the U.S. with some individuals from the different communities. These households contain migrants who return home each year as well as those that have settled abroad permanently.

As of November 1996, the dataset contained 7,143 households interviewed in Mexico and 516 surveyed in the United States. The refusal rates for the first 30 communities averaged 6.5% with peaks as high as 15%. Of the households interviewed, 3,346 of the head of households were U.S. migrants at some time during their lives.[9]

Methodology

The presentation of this section will be to first describe the general model and how the event history files were created, as well as to describe the data that are analyzed. The discussion will then turn to the diagnostic tools used to determine the shape of the hazard and a description of the empirical models that were estimated. The analytic strategy for adding the covariates was to first estimate the most liberal model with no covariates and progressively control for variables hypothesized to soak up the effect of networks. The final part of this section will be to describe and report the findings.

By examining the father and the eldest son, the household is located in one of four mutually exclusive states of migration at any one point in time. The event of interest begins

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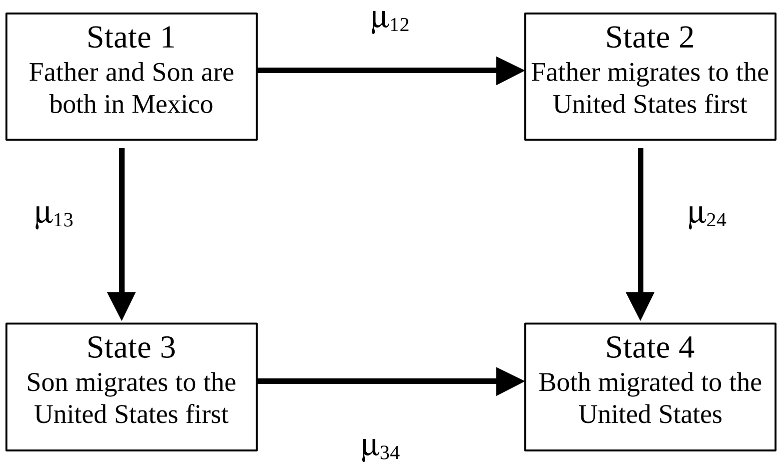
[9] For more information on the limitations of the Mexican Migration Project, the reader can turn to Massey and

when either father or son reports that they first migrated to the United States. The father-son specification effectively rules out the selectivity hypothesis. Of course there may be other people, familial or otherwise, which influence either the father or son to migrate, so this model specification may seem arbitrary but it allows me to isolate the network effect between just these two people. For the sake of simplicity, only the first migration is examined in this multi-state model so that the household can only move through the model unidirectionally.

State 1 is defined as when father and son reside in Mexico and have never migrated; state 2 is defined as when the father has migrated and the son has never migrated; state 3 is defined as when the son has migrated and the father has never migrated; and state 4 is defined as when both father and son have migrated to the United States, as illustrated in Figure 1:

Durand's article (Durand and Massey, 1992), as well as Appendix E.

Figure 1) **A Four State Event History Model**



For purposes of notation, the hazard, or risk, will be specified as μ. So the hazard for transition 1→2 will be expressed as μ_{12}. If knowing someone at the point of destination increases your risk of migrating to that country, then one would expect that the risk of migrating from transition 2→4 (son following father) to be higher than the risk associated with transition 1→3 (son going first) across all units of time. Similarly one would expect transition 3→4 (father following son) to have a higher risk associated with its transition than transition 1→2 (father going first) if networks played a significant role in affecting international migration.

On the other hand, if common causes explain the differences, then one could argue that by controlling for these variables the differences in the observed hazards should become equal. Therefore the general strategy for this analysis was to progressively control for variables which are hypothesized to explain away the network effect, such as human capital variables and common causes.[10] Because the majority of the households do not leave state 1, there is a potential mover-stayer problem—which refers to the question that there may be something substantively different from the population that moves through the system versus those who stay in an individual state.[11]

The creation of event history models requires two components: (1) failure, which denotes whether or not a particular event occurred, in this case it represents migration to the United States, and (2) duration, time period until the event occurred, if it occurred. In order to analyze the hazard of each transition, spells were created to represent the duration. Spells represent the time until the event occurs. This involves specifying a time of origin (T_o) to create a beginning point from which to calculate the duration of the event and then transforming that information into a state-period file. Time until event is operationalized in years since it is the smallest unit available from the dataset.

T_o is defined as the year in which the child of the household head turns 15 years old. This particular age is chosen because, arguably, it is the time in an individual's life where migration could occur with some degree of self-agency. If the father migrated before the son turned age 15, then that household was automatically placed into state 2 and a dummy variable was created to represent that household—although these cases do not contribute to [12], this method keeps both the father and the son simultaneously in the risk set.

[10] Two critical assumptions of this competing risk model is that of independence—which refers to the idea that the households do not influence each other's migration probability and, secondly, that those households which go from 1-3-4 are no different from those which go from 1-2-4.

[11] An attempt to control for the Mover-Stayer problem failed to produce reliable estimates.

The complete dataset includes 52,870 individuals. After removing the individuals who are not of interest for this study, the sample universe constituted 6,072 people or 3,036 father-son pairs. The process of selecting these individuals is discussed in the following paragraphs.

There are ten households in which a male is the spouse of the head of household. It is assumed that these males are the fathers of the oldest son in the household and therefore, were recoded as head of household. In 939 cases, the head of household is female. All females were deleted from the dataset since the focus is on father-son networks (18,937 individuals). Non-head of household (8,803 individuals) and children other than eldest son (11,399 individuals), were also excluded to isolate father and oldest son. At this point there remains 11,374 individuals, or 5,687 father-son pairs. However, based on the assumption that migration prior to age 15 is not an independent decision of the individual, those cases in which the father or son migrated prior to age 15 (290 individuals) or who were less than 15 (2,252 individuals) at the time of the survey were not included.

Other cases not included involved those households in which either father or son was born in the United States (13 individuals) and those households that were interviewed in the United States (385 individuals). The latter action is justified because it is not clear from the data whether responses referred to Mexican or U.S. years of education. Since this study controls for human capital variables, it is important to gather information only on Mexican education. Cases with unknown education (3 cases), occupation (72 cases), year of birth (36 cases), and year of migration (15 cases) were dropped. Those individuals within a household that are do not have a natural pair after the previous steps, for example a father without a son or a child without a father, were eliminated from the study (4,593 cases). The remaining 6,072 individuals represent a father and a son from each household or 3,036 father-son pairs.

Table 1 describes the distribution of the households from the communities of origin after selecting the pairs to be analyzed:

Table 1) **Communities of Origin from the Father-Son Pairs**

	Frequency	Percent
Guanajuato	706	23%
Jalisco	680	22%
Michoacan	622	20%
Nayarit	130	4%
Zacatecas	413	14%
Guerrero	36	1%
San Luis Potosí	364	12%
Colima	85	3%
	3,036	100%

The obvious overrepresentation of Guanajuato, Jalisco and Michoacan represents stages in the survey design. But they also coincide with the areas that have sent the most migrants, historically (Bean et al., 1997).[12] However, examining these aggregate statistics can be misleading. For example, if all households that transitioned from state 1 to state 2 originated in Colima, then the estimates may be biased. Before examining the more detailed information of the characteristics of the households by survey year and community for each transition (Appendix D), it is necessary to first explain how the households were assigned to the states, which requires an understanding of the creation of the spells.

[12] Recent waves of the Mexican Migration Project have sampled other provinces, and indeed future analysis will incorporate the new information into the model.

To formulate the spells, the states first need to be identified and a timeline developed to determine the length of time the household remains in each state. The household begins in state 1 at the time the son reaches the age of 15, unless the father migrates before this period. If the father migrates prior to the son turning 15 years, the household is placed directly in state 2. Given the information regarding the year of migration (yrus1) for both father and son, it is now possible to determine whether the household entered state 2 or state 3. If the year in which the father migrated is less than the year the son migrated, or the son did not migrate, then the household transitions to state 2. If the year the son migrated is less, then the household enters state 3. It is possible for the household to transition to either state 2 or state 3 but not both. The flow of migration for the household moves either from state 1 to state 2 to state 4 or from state 1 to state 3 to state 4, depending on whether it is the father or the son that migrates first. It is also not necessary for the household to reach the state 4; the household may become censored in any of the states. To enter state 4, the household either transitions from state 3 or state 2. To enter state 4 from state 3 the son migrated first and the father follows which is calculated by the father's year of migration, given the household is already in state 3. To enter state 4 from state 2 the father migrated first and the son follows which is calculated by the son's year of migration, given the household is already in state 2. Once the transitions of the household are determined, a timeline is developed so that the durations utilized in creation of the spells can be derived.

The timeline begins with T_o, which is defined as the year in which the son turns 15 years old, so it is calculated per household using the variable for the year in which the son is born (yrborn) and adding 15 years. The times for the subsequent states are then calculated and placed along the timeline. These time values will then be utilized in the calculation of the durations of the spells.

At this point, new variables representing each state (state1, state2, state3 and state4) have been introduced, as well as a variable corresponding to the time value on the timeline (time1, time2, time3 and time4). The number of the state is reported as the value for the state variables. Those variables, in which the household did not enter that particular state, will be represented by a period. Since this would result in difficulties in creation of the spells, additional variables are created that collapse the state and time variables (state1x, state2x and state3x). Therefore, state1x now represents the first state the household entered, which could be state 1, 2, 3 or 4; state2x could be state 2, 3 or 4; and state3x could be only state 4. Of course, if the household remained in the first state, state2x and state3x would hold a period, which are deleted during the formation of spells.

Spells are designed to transition the data to a state-period format that can be read by CTM. The first process is to generate the spells by calculating the duration utilizing the timeline developed earlier. For example, spell1 is generated by computing the difference between time2x and time1x. The data are then expanded by this value so that a line of data now represents one value of time for the household within that particular state. Once this process is completed for each of the spells (spell1, spell2, spell3), each line of the file now contains a value that represents the state the household is in (ksta), a value that is 0 unless this line is the final line for the household (lsta), and the covariate values. The lsta variable is a value for CTM that signals the end of the household. Once the data are expanded, the file of 3,036 households is prepared for use in CTM.

The transition matrix in Table 2 is provided to represent how the 3,036 households moved through the multi-state system.[13]

Table 2) **Transition Matrix for Father-Son Pairs**

		1	2	3	4
1	Count	1,381	118	308	15
	Mean Duration	14.58	8.28	8.59	9.40
2	Count	0	719	0	606
	Mean Duration	0.00	13.81	0.00	7.25
3	Count	0	0	294	21
	Mean Duration	0.00	0.00	9.46	4.76
4	Count	0	0	0	642
	Mean Duration	0.00	0.00	0.00	1.00

The table is read from the vertical to the horizontal axis. The first cell in the upper left-hand corner, for example, expresses that 1,381 households started in state 1 and remained in state 1. In the following column it says that 118 households went from state 1 to state 2. From this table, we can discern the number of households that each transition represents: 118 households transitioned from state 1 to state 2; 308 households transitioned from state 1 to state 3; 606 households transitioned from state 2 to state 4; and 21 households transitioned from state 3 to state 4.

This provides an idea of how many cases made the transitions or became censored in states 1, 2 and 3. While this information is important, it is helpful to understand the state in which the households began, to which states they transitioned, and in which state they concluded. For a precise exposition of how the cases moved through the model refer to Table 3:

[13] Continuous Time Multi-state Multi-spell Models (CTM) 1987 was used to estimate the model. This program was written by George Yates.

Table 3) **Household Flow Chart**

Transitions	Numbers
S_1	1,381
S_2	626
S_3	7
S_4	0
S_1S_2	93
S_1S_3	287
S_1S_4	15
S_2S_4	581
S_3S_4	0
$S_1S_2S_4$	25
$S_1S_3S_4$	21
Total	3,036

$S_1S_3S_4$ is read as 21 households started in state 1 and moved to state 4 through state 3. 1,207 households (S_2 and S_2S_4) started in state 2, which denote those cases where the fathers migrated before the son turned 15 years old. The 7 that start in state 3 represent sons that migrated to the U.S. the year they turned 15 years old. The S_3S_4 is zero because the 7 who started in state 3 are not joined by their fathers, so the household does not move to state 4. The figures represented in Table 2 are also clearly defined in Table 3. For example, S_1 is 1,381 cases that never moved beyond state 1. The 118 cases that transitioned from state 1 to state 2 are represented as the 93 in S_1S_2 and the 25 in $S_1S_2S_4$. The 606 in transition 2→4 are defined by the 581 in S_2S_4 and the 25 in $S_1S_2S_4$. All of the 3,036 father-son pairs are included in the event history analysis whether they transitioned through the model upon migration or whether they were censored.

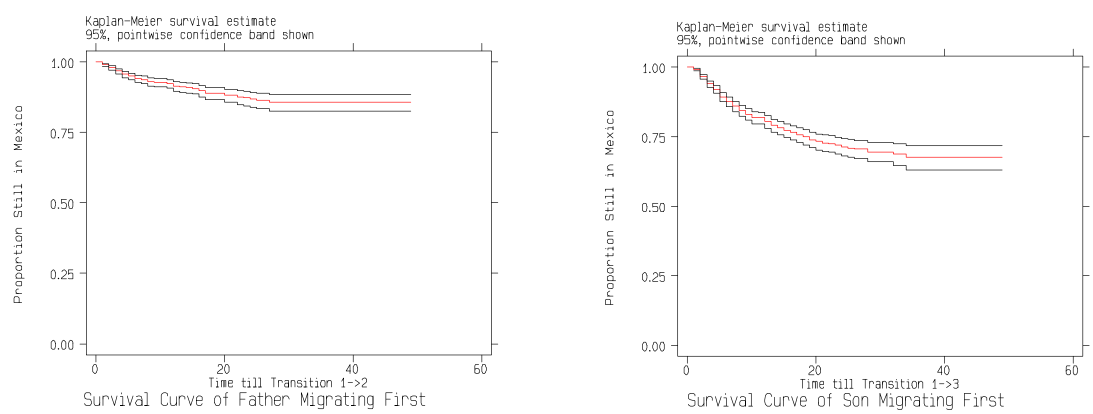
Presentation of the Model and the Estimates

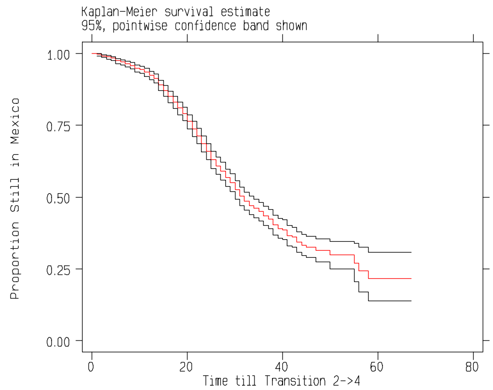
All of the standard approaches to event history analysis or survival analysis are assumed to be probabilistic. That is, the times at which the events occur are assumed to be from some underlying process. So one way of examining the time to migration distribution is to look at the simple survival function:

(eq 11) $$S(t) = \Pr\{T>t\} = 1 - F(t)$$

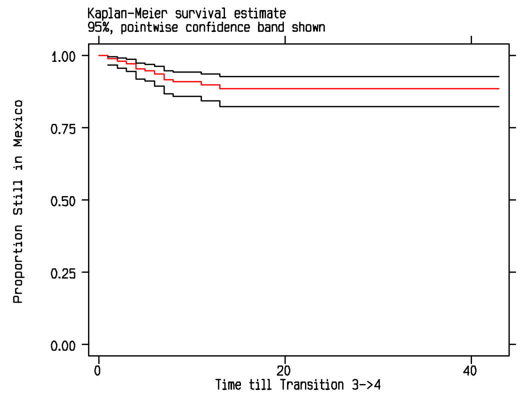
Below are the graphics obtained by looking at the Kaplan Meier survival table estimates—which show the probability of 'surviving' beyond time *t*. For this exercise, failures are defined as when someone migrates and censored variables are defined as when they do not migrate prior to the survey year. Although this does not allow an inspection of the hazard directly, it is one descriptive tool to diagnose the data. For purposes of illustration, the survival curves presented are nested between a Greenwood 95 percent confidence band.

<u>Figure 2) The Kaplan Meier Survival Estimates with a Greenwood 95% Confidence Band for Transitions (1→2), (1→3), (2→4), and (3→4)</u>





Survival Curve of Son Following Father



Survival Curve of Father Following Son

The information depicted in the Kaplan Meier Survival curves are shaped as expected. The relatively slight decreasing curves for transition 1→2 and 1→3 arise from the fact that most of the households in the survey do not migrate to the United States during the period examined. Also, it seems that the sons have a higher risk of following the father (μ_{24}) than the father following the son (μ_{34}). So although there is a low probability of migrating from the sample in general (transition 1→2 and transition 1→3), for those that have migrated there seems to be a high chance that the son will follow the father.

The survival function however, does not illustrate what the underlying hazard may look like because the function of the hazard is defined as an instantaneous value that can be greater than one:

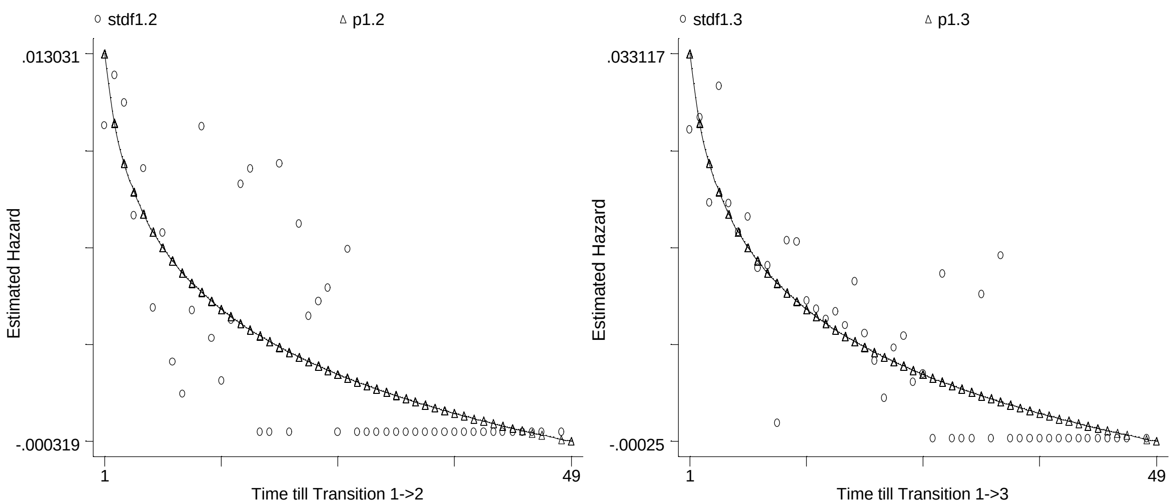
(eq 12) $$h(t) = \lim_{s \to 0} \Pr(t, t+s)/s$$

But the survival function is related to the hazard in the following way:

(eq 13) $$S(x) = \exp\left(-\int \mu(y)dy\right)$$

Therefore one way of estimating the form of the hazard is by graphing the negative log of the Kaplan Meier Survival. In terms of the data, those that did not make the transition are assumed to be censored. Cases are then sorted by time for each transition (1→2, 1→3, 2→4, and 3→4) and the negative log of the Kaplan Meier survival estimate is calculated for each case. Then the differences between successive cases are divided by the change in time. In summary, the graphics in Figure 3 represent the best estimate of the functional form of the hazard.

<u>Figure 3) This is the standardized -ln(km) against time for all the transitions[14]</u>



Estimate of the Hazard Function for Transition 1->2 | Estimate of the Hazard function for Transition 1->3

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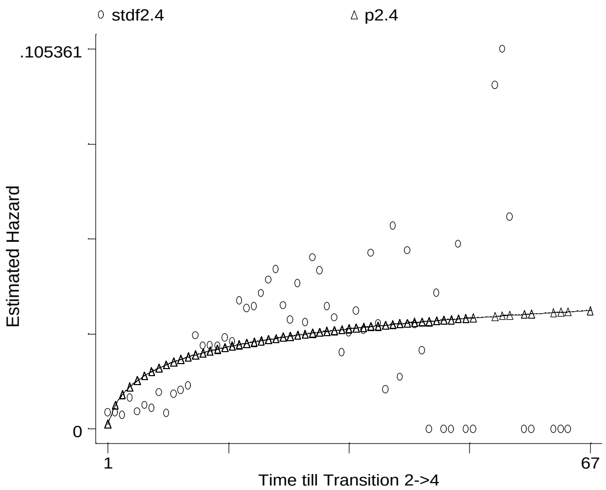
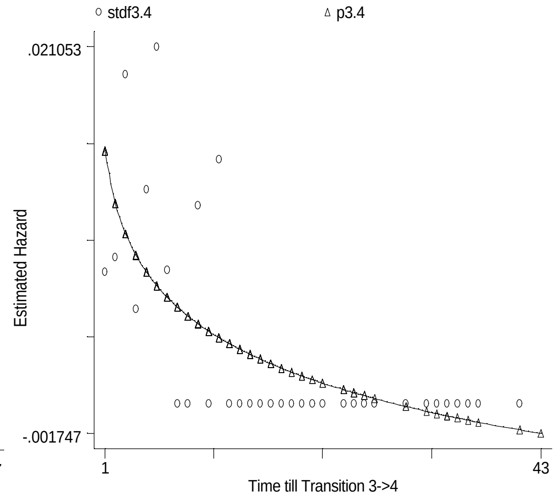
[14] To create the smooth line the regression coefficient β is estimated, then a separate equation which resembles the Weibull: Y=β*ln(t) is run. The predicted values from this second regression are then drawn through the graph to produce the curve.



Estimate of the Hazard Function for Transition 2->4



Estimate of the Hazard Function for Transition 3->4

However it needs to be kept in mind that censored cases for transition 1→2 might not migrate, but it is possible that the household made the 1→2 transition or 1→3 transition after the survey period. In order to estimate these hazards, both cases were treated as if they were censored for each particular transition. Transition 1→4 is excluded from this analysis.

As the graphics suggest, the functional form of the hazard closely approximates the Weibull Function, which is a flexible model. As stated by Teachman, “The Weibull regression model has not received as much attention as the exponential, but it may prove attractive in some applications since it can model monotonically decreasing or monotonically increasing hazard functions” (Teachman, 1983, pg. 277). [15]

For a multi-state model, the general Weibull expression is expressed as:

<u>Weibull Function</u>

(eq 14) $$\mu_{hijk}(t_j)=\exp(\alpha_{k} + \gamma_j \ln(t_j) + \delta_k X_{jk} + \beta_k Z_j + \theta_j W_j)$$

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[15] Confidence in the model selection, at least for the coefficient estimates, is additionally supported in the literature; as stated by Allison, “Much experience with these models suggest that the coefficient estimates are not terribly sensitive to the choice of the hazard function” (Allison, 1984, pg. 33).

Transitions are made from state *h* to state *i* for household *j* and individual *k*. *t* is time with parameter *g* for household *j*, *X* and *Z* are the mean values for the covariates, and *a*, *g*, *d*, *b*, and *q* are estimated parameters. To estimate the transitions simultaneously the Maximum Likelihood procedure is utilized in CTM.

<u>Distribution, Recodes, and the Employment of the Covariates</u>

The covariates are classified into two major groupings: Human Capital variables and Common Cause variables. The first consists of age, education, occupation and documentation. The latter group consisted of community type, ownership of land, business, and home, the period of migration, and whether the father migrated before the son turned 15 years old.

Decisions made concerning recoding the covariates resulted from the distributions of the variables within the transitions. The transition means for the covariates per transition are illustrated in Tables 5-6. Age is defined as the age of the individual at the time the household enters the state. For example, age for transition 1→2 is the age of the father when the household enters state 1. Father's age was categorized as 42 years and under or over 42 years old for transitions 1→2 and 3→4. However, because there is an asymmetric distribution of ages for the son, the dummy variables were coded differently. Dummies for the son's age included those between the years 15-20 and 21-25. The omitted category is if the son's age is 26 years or greater. Since the clock starts when the son turns 15, age was not controlled in transition 1→3 because by construction all the sons have an age of 15 upon entering state 1. For those households in which the father migrated prior to the son turning 15 years old, that household was put into state 2 and the son's age is 15 for transition 2→4. Additionally, for those households in which the father migrated prior to the son turning 15 years old, a dummy variable was created and coded 1.

For transition 1→2, dummies were created for the father having 0-3 years of education and 4-9 years of education with an omitted category of 10 or greater years of education. But for transition 3→4 the variable of 0-3 years of education for the father was used with all other categories omitted. For the son's education covariates representing between 4-9 years and 10 or greater were used consistently, with the 0-3 years of education category omitted (for both transitions 1→3 and 2→4). This points to the fact that fathers have a different distribution of years of education in general, but within transition 3→4 in particular. The descriptives for the sample averages are presented in Table 4.

The employment variable was also distilled into a dummy variable and labeled "skilled employment." The skilled employment classification includes professionals, technicians, office workers, salespersons, farmers, and government workers. Unskilled employment contains jobs such as day laborers, domestic workers, hotel and restaurant workers, and unskilled machinery operators.[16] The omitted categories for this analysis are unemployed, student and unskilled.[17] These classifications were utilized for the father in transitions 1→2 and 3→4, as well as the son in transitions 1→3 and 2→4.

For the common cause variables, the characteristics of the communities were used: metropolitan area, small urban area, town, and ranch. The omitted category is the small urban

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[16] Data used came from persfile. The lifefile has better job histories, but only for the head of household and not for the children. Further analysis could link the lifefile with the information from the persfile.
[17] One issue with the occupation variable is that the response refers to the present occupation at the time of the survey, which may not necessarily be the same occupation that the person had upon entering the state.

area. Land, business and home owned are three additional covariates included as common cause variables in all transitions.

The period variable arose from the concern that there were major policy changes within the U.S. regarding Mexico over the period these pairs first migrated. In 1964 the Bracero program was terminated and a quota was enacted to specify the number of immigrants allowed to enter the U.S. from Mexico. The previous 50% immigrant slots set aside for labor market needs were reduced to 20% after 1965 (Briggs, 1984, pg.68).

In 1986 the Immigration Reform and Control Act (IRCA) attempted to limit undocumented immigration by implementing an amnesty program while also sanctioning employers hiring undocumented immigrants. Hence, after 1965 the restrictions on immigration increased until IRCA was passed. However, because of the amnesty program more immigrants became eligible for migrating to the United States under the family reunification priority (Yang, 1995).

How the network effect changes with policy shifts is debated. Proponents of network theory hypothesize that more restrictive policies might increase the importance of networks. Assuming a constant flow from Mexico and increasing restriction from the United States, it could be argued that networks became more effective during the increased restriction in order to migrate across the border safely. There are two ways in which this could have played out. First it is possible that the potential migrant needs to use his/her family connections to take advantage of the family reunification aspect of the law. Secondly, for those migrants without papers it can be argued that the social networks are even more important to help them obtain information for safe passage, i.e., identification, jobs, housing etc.

Opponents of this hypothesis conclude that the restrictive laws explicitly privilege education as a means of passage to the United States, and thus espouse that the restrictive immigration policy during these periods efficiently stems migration—regardless of networks. So this argument places more weight on not 'who you know' but 'what you know'. Therefore, the period effect is added to this model to test the effects of networks under the periods of greater restriction. The last control, the undocumented variable, is coded as 1 if they did not have papers upon entry to the U.S. This variable, in conjunction with the period variable, can be used as a test for the hypothesis that more restrictive public policy on immigration would increase the need for more efficient networks.

After recoding the variables, CTM was then utilized to obtain model estimates (Table 7-Table 10) and those values were used to graph the predicted function of the hazard (Figure 4- Figure 9). Furthermore, the respective hazards per transition were also used to create life tables, which help examine the mean time of staying in Mexico (Table 11 and Table 12). The formula used to create the graphics and life tables from the predicted values is:

(eq 15) $$\mu(t)=\exp(\alpha + \gamma\ln(t) +\beta_1X_1 + \beta_2X_2+..+\beta_nX_n)$$

where *b* represents the predicted values for the individual covariates and *X* represents the covariate mean. The results are presented in Figures 2-6.

The models graduate from the most basic, with no covariates, to one with all the controls including unmeasured heterogeneity. The Unmeasured Heterogeneity model, with two points of support, controls for unmeasured common causes between the father and son. CTM controls for unmeasured heterogeneity by using the Heckman and Singer method. An attempt was made to examine a model controlling for the mover-stayer problem and a separate model to test if there was an interaction effect with the period variable, but both efforts failed to converge. The statistical significance for the coefficients was set at the .05 level.

The Log Likelihood Ratio test was also performed for every model with respect to the prior. The equation used for calculating Log Likelihood Ratio test is:

(eq 16) $$\text{LR Test}=2*(\text{Log Likelihood}_{Ho} - \text{Log Likelihood}_{Ha})$$

Where Log Likelihood $_{Ho}$ is equal to the previous model and Log Likelihood $_{Ha}$ is the model of interest (See Tables 7-10).

Results

In terms of the coefficients, not having legal documents is statistically significant at the .01 level and positive for both fathers and sons across all models. The period of migration between 1965-1986 is positive and statistically significant in the saturated model for all the transitions. These findings are consistent with recent work by Donato, Durand and Massey (1992) in which their study found that restrictive immigration legislation had little effect on reducing undocumented immigration.

With respect to education, the son's covariates are statistically significant at the .01 level and positive with respect to having less than 3 years of education for both transitions ($1\rightarrow3$ and $2\rightarrow4$) across all the models (Table 8 and Table 9) contrasting this for father's education which had no significant effect. Interestingly, owning land is significant at the .05 level and positively related to the hazard of migrating for transition $1\rightarrow2$ (Table 7), however for transition $1\rightarrow3$, owning land is significant at the .05 level but is negative (Table 8). One explanation for these results is that it could be that fathers who own land and migrate first (compared to the eldest son) are more likely to migrate if they own land, perhaps in an effort to diversify the family income; but the caveat is that the sons who migrate first (compared to the father) are probably less likely to migrate if the household owns land so that they can tend to the property.

Owning a home is significant at the .05 level and negative for the transition 2→4 (Table 9). This seems to mirror the story mentioned, in that if a household does send their sibling abroad after the father, he is less likely to go if the household owns a home.

Having a skilled profession is negatively related and significant at the .05 level in the saturated models for transitions 1→2 and 1→3 (Tables 7 – 8). This finding suggests that if the individual is an asset to the household, that person may be less likely to move. It might be that their skills are more valuable to the household in Mexico than if that person had migrated. Originating from a ranch community, controlling for the other types, is significant at the .01 level and positive for the sons following the father (Table 9). So that the household will send their son after their father, more likely, if the household is from a ranch.

However residing in a metropolitan area is significant at the .01 level and positive for the fathers following the son (Table 10). This suggests that there is a difference process which selects which families migrate from cities versus ranchos. Looking at the age distributions for where the father follows the son, one story which can be interpreted is that since the household does not need someone to tend to the property, the fathers are joining the son. This highlights that households which migrate from cities are characteristically different in their social relationships compared to households which are migrating from the ranchos.

In any case, the more important results are derived from the inspection of the predicted hazards (Figure 4 – Figure 9). Having a household member who has migrated to the U.S. (father or son) is associated with a greater risk of migration compared to households who have not yet sent either the father or the son. The no covariate model for the fathers illustrates that the risk of the father following the son is higher than the father going first, but this changes after 25 to 29 years. However once the human capital, common cause, or the unmeasured heterogeneity is controlled for, the hazard is higher for all points in time of the father following the son (μ_{34}) than for a father who migrates first (μ_{12}).

There is a slightly different trend in the examination of the son's hazards. With the no covariate model, the risk of a son migrating after a father (μ_{24}) is higher at all points in time compared to households where the son migrates first (μ_{13}). However, this result changes once the controls are added (Table 5 – Table 9). For human capital controls and the common causes, this balance seems change at approximately 17 years; and it shifts even further between 25 and 33 years for the period model and the heterogeneity models respectively (Tables 11 – 12).

For the father's case, it is clear that having a son who migrated first to the United States is associated with a higher hazard (μ_{34}), than if the father were to migrate first (μ_{12}), even after controlling for all the effects. Although in the son's case this difference seems less pronounced with an overlap occurring between 17 and 33 years, there is still a higher hazard for the son migrating second (μ_{24}) as opposed to the son going first (μ_{13}). This illustrates that, even when controlling for selection (father-son) and common causes (community characteristics) or individual traits (human capital), having a family member migrate first to the U.S. gives the person who might follow second a higher risk of migrating compared to households who did not send a member first.

Lastly, life tables were created with the values of the Weibull implemented as the "time specific migration rates" (qx). The life expectancies (E_x) can be read as the average time expected to stay in Mexico after entering a specific state.

For example, the average 'life expectancy' or years till migration for a father who will migrate first (transition 1→2) from 0-1 years in state 1 is 15.74 years and decreases monotonically. The same could be said for the son who migrates first (transition 1→3), whose average years till migration is 10.91 for the first year interval in state 1. As was mentioned before, for those who had a son or father who migrated first, the years till migration is less—particularly for the father (Table 11). So the average years till migration from state 3 is 7.15 compared to 15.74, and it is 8.74 for the sons compared to 10.91.

Discussion and Conclusion

The goal of this study is to test network theory with more advanced techniques than what has been done in the literature to date. By transforming the available information to allow for a multi-state event history study, my goal was to be able to control for both measured and unmeasured factors, which may confound simple linear model analysis of migration. Changing the focus of migration away from a discrete event, such as a logit analysis, this paper attempts to advance our knowledge in terms of new methods of analyzing migration. As stated by Massey, "Network Theory should move beyond dichotomous indicators of network connections to measure networks as a form of social capital that varies continuously . . ." (Massey et al., 1994, pg.740).

The empirical logic of this study was to examine the effect of networks versus having no networks, progressively controlling for factors that theoretically challenge the differences in the predicted hazards. The findings from this study provide additional evidence that social networks explain a higher rate of migration than not having them, net of common cause and self-selection. The predicted values indicate that the hazard of the father following the son (μ_{34}) is higher than if the father migrates by himself (μ_{12}), at least initially, while it is consistently higher for the son following the father (μ_{24}) when compared to the son migrating first (μ_{13}). This result seems to maintain itself even after controlling for human capital variables (education, occupation, age and documentation), which may underscore that the decision process is largely a household one.

Indeed social networks are not a reason for migration, people move for a multiple of reasons not directly addressed in this paper. But this research buttresses previous findings supporting network theory, and allows us to highlight with more confidence that social relations, particularly between fathers and sons, may act as a significant force in explaining migration. Perhaps the network effect works through reducing the cost of moving, either monetarily, psychologically, or socially. Additionally, it could act as an information feedback mechanism for the community. So once migration has started, the character of the point of origin is changed with the association of people at the point of destination, and this increases the risk for everyone in the household to migrate in comparison to households which lack that link (Portes, 1995).

There are many other directions that future studies should take to examine this issue more thoroughly. In terms of this particular information, further analysis could examine the data using alternative techniques with the missing information, or try to fit other functional forms—such as a non-parametric model, or perhaps deal with the information differently by constructing time-varying covariates. Additionally, the effect of networks could extend to other people within the family, such mother-child or siblings, so further studies could use the information provided by the Mexican Migration Project to also look at these relationships.[18] More broadly, further research needs to not only include women in the study of networks[19] (Boyd, 1989), but this kind of exercise also needs to be utilized to analyze other immigrant groups. As Massey stated, after a review of the studies on networks,

> "Nonetheless, results thus far have come from a relatively small number of community case studies and a small number of quantitative analysis from a limited range of countries and datasets. In particular, more and better research on non-Mexican samples is clearly needed to confirm the generality of findings" (Massey et al., 1994, pg. 733).

And as it relates to the general field:

> "Our review uncovered other deficiencies in the literature. Far too much research is centered in Mexico, which because of its unique relationship to the United States may be unrepresentative of broader patterns and trends. Even within Mexico, a great deal has been generalized from a small set of studies concerning a handful of sending communities conducted by relatively few investigators. Within Mexico, new researchers need to gather information from a broader sample of communities. Within the field generally, more attention needs to be devoted to other prominent sending countries, such as the Philippines, the Dominican Republic, Jamaica, Colombia, El Salvador, Korea, and China" (Massey et al., 1994, pg. 739).

Additionally, an implicit assumption of this work is that having a social tie to a person necessarily is a good source of information, but indeed associations need not always be positive.[20] Further work should examine how social capital is transformed between people over time. Particularly, as put forward by Boyd, "To better understand the dynamic of migration networks, two questions require answers: 1) why and when do personal networks

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[18] Miguel Ceballos has studied siblings with the same model and found a network effect as well.

fail to emerge; and 2) under what conditions do networks weaken and/or disappear" (Boyd, 1989, pg. 655).

More importantly, however, is that even though networks seem to matter, knowledge regarding peoples' motivation to migrate is not explained by this theory or this study in particular. As Philip Q. Yang stated in his book Post 1965 Immigration to the United States:

> "One of the inadequacies of immigrants' network theory lies in its inability to adequately address the motivation of immigration. This approach primarily answers why immigrants are able to come but gives little consideration to why they want to do so. Motivation is important, as stressed in the homily, 'Where there is a will, there is a way.' Conversely, if people are not motivated to leave their countries, they will not go, even though they may have the means to do so. . . In short, immigrants network theory is not sufficient to capture all the important factors that reflect the means of migration (Fawcett and Arnold)"**-** (Yang, 1995, pg.55).

In conclusion, this study reaffirms past research that finds that a social tie to someone that has migrated represents an important factor in migration. But it adds to the literature by proposing and utilizing a multi-state event history model, developed by Palloni and Massey, which allows the researcher to control for both unmeasured and measured common causes, as well as rule out the possibility of self selection.

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[19] Boyd argues persuasively that the network hypothesis would be augmented if studies could also examine the role of women.
[20] This line of argumentation is credited to Alberto Palloni.

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Appendix A

Table 4) **Means for All Households**

	Fathers			Sons		
	Number	**Means**	**Std. Dev.**	**Number**	**Means**	**Std. Dev.**
Human Capital						
Completed 0 to 3 years of Education	1,903	0.6268	0.4837	516	0.1700	0.3757
Completed 4 to 9 years of Education	946	0.3116	0.4632	1,704	0.5613	0.4963
Completed 10+ years of Education	187	0.0616	0.2405	816	0.2688	0.4434
Unemployed	429	0.1413	0.3484	110	0.0362	0.1869
Student	0	0.0000	0.0000	382	0.1258	0.3317
Unskilled	935	0.3080	0.4617	1,126	0.3709	0.4831
Skilled	1,672	0.5507	0.4975	1,418	0.4671	0.4990
Father's Age at Survey is 43+ years	2,630	0.8663	0.3404			
Son's Age at Survey is 15 to 20 years				769	0.2533	0.4350
Son's Age at Survey is 21 to 25 years				589	0.1940	0.3955
Son's Age at Survey is 26+ years				1,678	0.5527	0.4973
Undocumented	783	0.2579	0.4376	807	0.2658	0.4418
Common Cause						
Land Owner	694	0.2286	0.4200	694	0.2286	0.4200
Home Owner	2,432	0.8011	0.3993	2,432	0.8011	0.3993
Business Owner	1,118	0.3682	0.4824	1,118	0.3682	0.4824
Metropolitan Area	833	0.2744	0.4463	833	0.2744	0.4463
Small Urban Area	822	0.2708	0.4444	822	0.2708	0.4444
Town	703	0.2316	0.4219	703	0.2316	0.4219
Ranch	678	0.2233	0.4165	678	0.2233	0.4165
Migrated before Son was 15 years				1,207	0.39756	0.4895
Period Effects						
Migrated prior to 1965	803	0.2645	0.4411	50	0.0165	0.1273
Migrated between 1965 and 1986	504	0.1660	0.3721	647	0.2131	0.4096
Migrated after 1986	54	0.0178	0.1322	239	0.0787	0.2693
Never migrated	1,675	0.5517	0.4974	2,100	0.6917	0.4619
Number of cases	3,036			3,036		

Table 5) **Means Used to Estimate the Weibull for Transitions 1 - 2 and 3 - 4**

	Transition 1 to 2			Transition 3 to 4		
	Number	**Means**	**Std. Dev.**	**Number**	**Means**	**Std. Dev.**
Human Capital						
Completed 0 to 3 years of Education	81	0.6864	0.4659	18	0.8571	0.3586
Completed 4 to 9 years of Education	31	0.2627	0.4420	3	0.1429	0.3586
Completed 10+ years of Education	6	0.0508	0.2206	0	0.0000	0.0000
Unemployed	25	0.2119	0.4104	3	0.1429	0.3586
Student	0	0.0000	0.0000	0	0.0000	0.0000
Unskilled	39	0.3305	0.4724	8	0.3810	0.4976
Skilled	54	0.4576	0.5003	10	0.4762	0.5118
Age 43+ years	24	0.2034	0.4042	15	0.7143	0.4629
Undocumented	88	0.7458	0.4373	16	0.7619	0.4364
Common Cause						
Land Owner	29	0.2458	0.4324	5	0.2381	0.4364
Home Owner	89	0.7542	0.4324	20	0.9524	0.2182
Business Owner	43	0.3644	0.4833	7	0.3333	0.4830
Metropolitan Area	30	0.2542	0.4373	4	0.1905	0.4024
Small Urban Area	34	0.2881	0.4548	7	0.3333	0.4830
Town	24	0.2034	0.4042	6	0.2857	0.4629
Ranch	30	0.2542	0.4373	4	0.1905	0.4024
Period Effects						
Migrated prior to 1965	17	0.1441	0.3527	2	0.0952	0.3008
Migrated between 1965 and 1986	72	0.6102	0.4898	8	0.3810	0.4976
Migrated after 1986	29	0.2458	0.4324	11	0.5238	0.5118
Number of cases	118			21		

Table 6) **Means Used to Estimate the Weibull for Transitions 1 - 3 and 2 - 4**

	Transition 1 to 3			**Transition 2 to 4**		
	Number	**Means**	**Std. Dev.**	**Number**	**Means**	**Std. Dev.**
Human Capital						
Completed 0 to 3 years of Education	82	0.2662	0.4427	139	0.2294	0.4208
Completed 4 to 9 years of Education	188	0.6104	0.4885	378	0.6238	0.4848
Completed 10+ years of Education	38	0.1234	0.3294	89	0.1469	0.3543
Unemployed	10	0.0325	0.1775	18	0.0297	0.1699
Student	0	0.0000	0.0000	4	0.0066	0.0810
Unskilled	168	0.5455	0.4987	373	0.6155	0.4869
Skilled	130	0.4221	0.4947	211	0.3482	0.4768
Age 15 to 20 years				600	0.9901	0.0991
Age 21 to 25 years				1	0.0017	0.0406
Age 26+ years				5	0.0083	0.0905
Undocumented	274	0.8896	0.3139	515	0.8498	0.3575
Common Cause						
Land Owner	75	0.2435	0.4299	226	0.3729	0.4840
Home Owner	243	0.7890	0.4087	511	0.8432	0.3639
Business Owner	101	0.3279	0.4702	201	0.3317	0.4712
Metropolitan Area	56	0.1818	0.3863	32	0.0528	0.2238
Small Urban Area	82	0.2662	0.4427	137	0.2261	0.4186
Town	94	0.3052	0.4612	196	0.3234	0.4682
Ranch	76	0.2468	0.4318	241	0.3977	0.4898
Migrated before Son was 15 years				581	0.9587	0.1990
Period Effects						
Migrated prior to 1965	16	0.0519	0.2223	33	0.0545	0.2271
Migrated between 1965 and 1986	195	0.6331	0.4827	437	0.7211	0.4488
Migrated after 1986	97	0.3149	0.4652	136	0.2244	0.4175
Number of households	308			606		

Appendix B

Table 7) **Transition 1 - 2 Weibull Model of Father Migrating First**

	Baseline No Covariates		Human Capital		Common Cause		Period Effects		Heterogeneity	
Intercept	-5.2844	**	-6.5050	**	-6.5526	**	-6.1680	**	-9.2751	**
	(0.2476)		(0.6877)		(0.7815)		(0.8302)		(1.0481)	
Gamma	-0.0144		0.4022	**	0.4140	**	0.3752	*	0.8414	**
	(0.1233)		(0.1440)		(0.1501)		(0.1497)		(0.1999)	
Completed 0 to 3 years of Education			-0.8982		-0.8786		-0.9392		-0.7467	
			(0.6405)		(0.6959)		(0.7422)		(0.7274)	
Completed 4 to 9 years of Education			-0.5432		-0.4411		-0.4180		-0.1962	
			(0.6561)		(0.7097)		(0.7544)		(0.7644)	
Skilled			-0.3077		-0.3927		-0.6171	**	-0.6192	*
			(0.1968)		(0.2129)		(0.2012)		(0.2507)	
Age 43+ years			-0.3610		-0.3624		-0.3974		-0.7532	*
			(0.2487)		(0.2680)		(0.2612)		(0.2990)	
Undocumented			4.5721	**	4.6032	**	3.8528	**	4.3288	**
			(0.2194)		(0.2270)		(0.2388)		(0.2968)	
Land Owner					0.3831		0.6397	*	0.8443	*
					(0.2580)		(0.2830)		(0.3733)	
Home Owner					0.0572		-0.1727		-0.4650	
					(0.2464)		(0.2233)		(0.3131)	
Business Owner					-0.0690		-0.0856		-0.2993	
					(0.2365)		(0.2085)		(0.2741)	
Metropolitan Area					-0.1726		-0.1519		-0.4737	
					(0.3104)		(0.2915)		(0.3495)	
Town					-0.1940		-0.4006		-0.3643	
					(0.2570)		(0.2370)		(0.3256)	
Ranch					-0.0265		-0.2327		-0.4380	
					(0.3082)		(0.3133)		(0.3865)	
Migrated between 1965 and 1986							1.0719	**	1.8258	**
							(0.2299)		(0.2717)	
Factor Loading									2.4843	**
									(0.4843)	
Negative Log Likelihood	5037.1643		3679.1132		3655.8455		3618.5008		3579.4656	
Degrees of Freedom			4		6		1		1	
-2(Model Difference Log Likelihood)			2716.1020		46.5355		74.6893		78.0705	

* p>.05; ** p>.01

Table 8) **Transition 1 - 3 Weibull Model of Son Migrating First**

	Baseline No Covariates		Human Capital		Common Cause		Period Effects		Heterogeneity	
Intercept	-4.4675	**	-8.0915	**	-7.9828	**	-7.9824	**	-9.8854	**
	(0.1762)		(0.3009)		(0.3653)		(0.3609)		(0.6256)	
Gamma	0.0611		0.5939	**	0.6337	**	0.6306	**	0.9147	**
	(0.0830)		(0.0903)		(0.0983)		(0.0992)		(0.1548)	
Completed 4 to 9 years of Education			0.5150	**	0.4978	**	0.5065	**	0.6175	**
			(0.1264)		(0.1403)		(0.1398)		(0.1744)	
Completed 10+ years of Education			0.6901	**	0.6535	**	0.7022	**	0.7422	**
			(0.2287)		(0.2414)		(0.2516)		(0.2732)	
Skilled			-0.2041		-0.2847	*	-0.2719	*	-0.3565	*
			(0.1153)		(0.1308)		(0.1322)		(0.1525)	
Undocumented			4.6213	**	4.6887	**	4.5866	**	4.8836	**
			(0.1923)		(0.2047)		(0.2117)		(0.2293)	
Land Owner					-0.3736	*	-0.3699	*	-0.3761	*
					(0.1612)		(0.1626)		(0.1790)	
Home Owner					-0.1591		-0.1697		-0.1961	
					(0.1395)		(0.1364)		(0.1755)	
Business Owner					0.1611		0.1584		0.1947	
					(0.1279)		(0.1279)		(0.1558)	
Metropolitan Area					0.0000		-0.0224		-0.1084	
					(0.1869)		(0.1877)		(0.2219)	
Town					-0.0630		-0.0853		-0.0769	
					(0.1745)		(0.1767)		(0.2149)	
Ranch					0.0204		0.0166		0.0385	
					(0.1761)		(0.1766)		(0.2196)	
Migrated between 1965 and 1986							0.1613		0.3327	*
							(0.1409)		(0.1610)	
Factor Loading									1.4172	**
									(0.2749)	
Negative Log Likelihood	5037.1643		3679.1132		3655.8455		3618.5008		3579.4656	
Degrees of Freedom			4		6		1		1	
-2(Model Difference Log Likelihood)			2716.1020		46.5355		74.6893		78.0705	

* p>.05; ** p>.01

Table 9) **Transition 2 - 4 Weibull Model of Son Migrating After Father**

	Baseline No Covariates		Human Capital		Common Cause		Period Effects		Heterogeneity	
Intercept	-3.0649	**	-5.9963	**	-5.9220	**	-6.2409	**	-7.8448	**
	(0.0961)		(0.4510)		(0.5513)		(0.5581)		(0.6353)	
Gamma	-0.0573		0.2870	**	0.3020	**	0.3282	**	0.6196	**
	(0.0468)		(0.0438)		(0.0461)		(0.0462)		(0.0777)	
Completed 4 to 9 years of Education			0.5739	**	0.5883	**	0.6687	**	0.8534	**
			(0.0917)		(0.0935)		(0.0883)		(0.1258)	
Completed 10+ years of Education			0.5585	**	0.6533	**	0.7889	**	0.7954	**
			(0.1696)		(0.1831)		(0.1869)		(0.1960)	
Skilled			-0.1119		-0.0753		-0.0772		-0.2210	
			(0.0895)		(0.0985)		(0.0922)		(0.1164)	
Age 15 to 20 years			0.2789		0.6057		0.7837		0.1210	
			(0.4414)		(0.6142)		(0.5882)		(0.6226)	
Age 21 to 25 years			-0.7618		-0.8893		-0.7412		-1.5754	
			(1.4201)		(1.5048)		(1.6152)		(1.7787)	
Undocumented			2.9644	**	2.8964	**	2.3734	**	2.6081	**
			(0.1162)		(0.1184)		(0.1265)		(0.1406)	
Land Owner					-0.0139		-0.0140		-0.0271	
					(0.0857)		(0.0832)		(0.1151)	
Home Owner					-0.1912	*	-0.1908	*	-0.2890	*
					(0.0951)		(0.0893)		(0.1303)	
Business Owner					-0.0398		0.0284		0.0278	
					(0.0791)		(0.0849)		(0.1122)	
Metropolitan Area					-0.4272		-0.4321		-0.4492	
					(0.2789)		(0.2676)		(0.2847)	
Town					0.1282		0.0155		0.2401	
					(0.1274)		(0.1211)		(0.1532)	
Ranch					0.3541	**	0.3331	**	0.5281	**
					(0.1247)		(0.1193)		(0.1473)	
Migrated before Son was 15 years					-0.3732		-0.4214		-0.2290	
					(0.3144)		(0.2781)		(0.2596)	
Migrated between 1965 and 1986							0.8185	**	1.0892	**
							(0.1018)		(0.1205)	
Factor Loading									1.5604	**
									(0.1918)	
Negative Log Likelihood	5037.1643		3679.1132		3655.8455		3618.5008		3579.4656	
Degrees of Freedom			6		7		1		1	
-2(Model Difference Log Likelihood)			2716.1020		46.5355		74.6893		78.0705	

* p>.05; ** p>.01

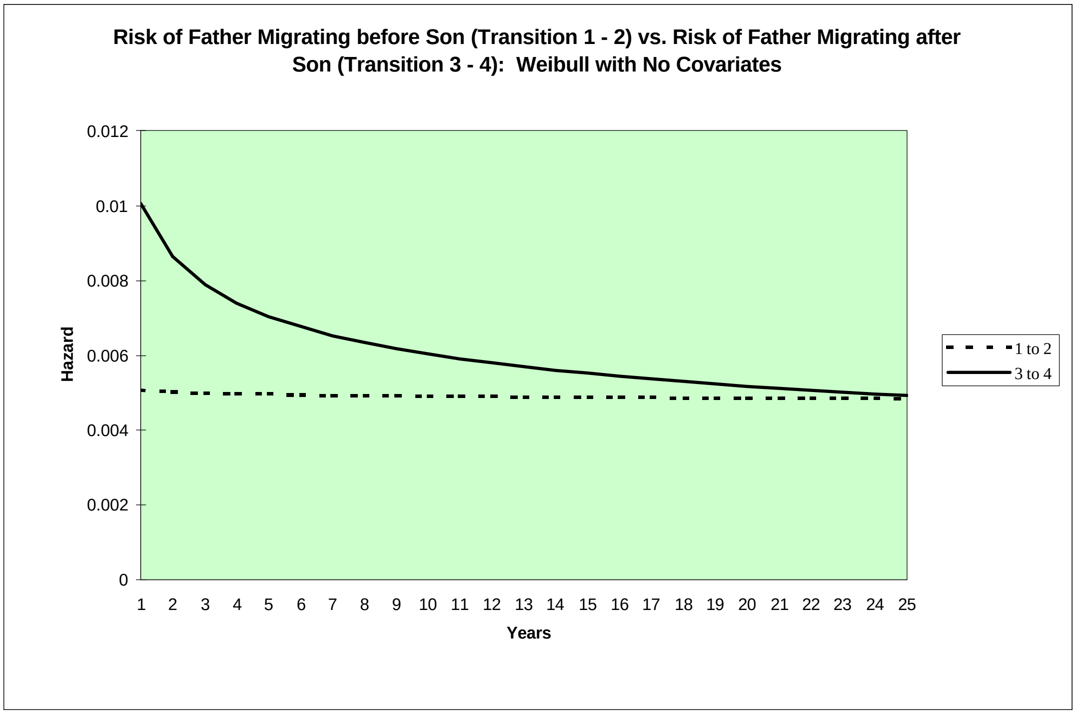
Table 10) **Transition 3 - 4 Weibull Model of Father Migrating After Son**

	Baseline No Covariates		Human Capital		Common Cause		Period Effects		Heterogeneity	
Intercept	-4.5986	**	-7.8601	*	-8.6599	**	-8.5703	**	-16.5489	**
	(0.4222)		(3.1088)		(2.4980)		(2.2903)		(1.8207)	
Gamma	-0.2224		0.5898		0.6748		0.7537		5.1741	**
	(0.2701)		(0.3876)		(0.5452)		(0.5117)		(0.7348)	
Completed 0 to 3 years of Education			0.5973		0.4062		0.2171		1.3911	
			(2.7946)		(5.1280)		(3.4626)		(1.4280)	
Skilled			0.0588		-0.0795		0.0666		2.6115	
			(0.5784)		(1.1201)		(1.5209)		(1.6300)	
Age 43+ years			-0.2663		-0.3100		-0.2088		-1.5696	
			(0.7975)		(0.9349)		(1.0146)		(0.9389)	
Undocumented			5.7347	**	5.9542	**	5.6459	**	18.9586	**
			(0.7609)		(0.9846)		(1.0597)		(2.6706)	
Land Owner					0.3701		0.2335		1.1028	
					(0.9445)		(1.1216)		(1.5951)	
Home Owner					0.6822		0.6020		-0.5388	
					(5.0462)		(3.5549)		(1.6552)	
Business Owner					-0.2695		-0.6957		-1.7485	
					(0.9951)		(1.0297)		(1.4378)	
Metropolitan Area					0.4882		0.7221		3.2320	**
					(1.3341)		(1.7032)		(1.2378)	
Town					0.0782		0.1882		0.6175	
					(0.8747)		(0.9069)		(1.2088)	
Ranch					0.4181		0.1042		-1.2715	
					(1.0535)		(0.9467)		(1.5542)	
Migrated between 1965 and 1986							0.8994		2.1939	*
							(0.9794)		(1.1124)	
Factor Loading									-12.5246	**
									(2.6270)	
Negative Log Likelihood	5037.1643		3679.1132		3655.8455		3618.5008		3579.4656	
Degrees of Freedom			4		6		1		1	
-2(Model Difference Log Likelihood)			2716.1020		46.5355		74.6893		78.0705	

* p>.05; ** p>.01

Appendix C

Figure 4) **No Covariate Model**



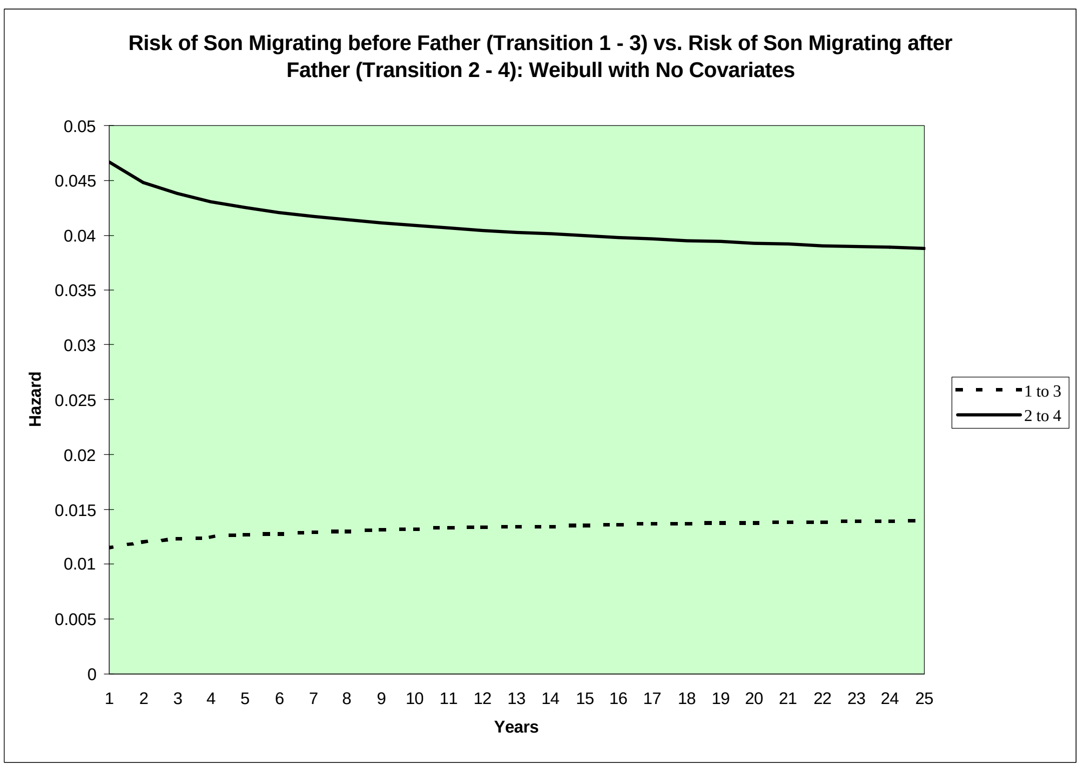
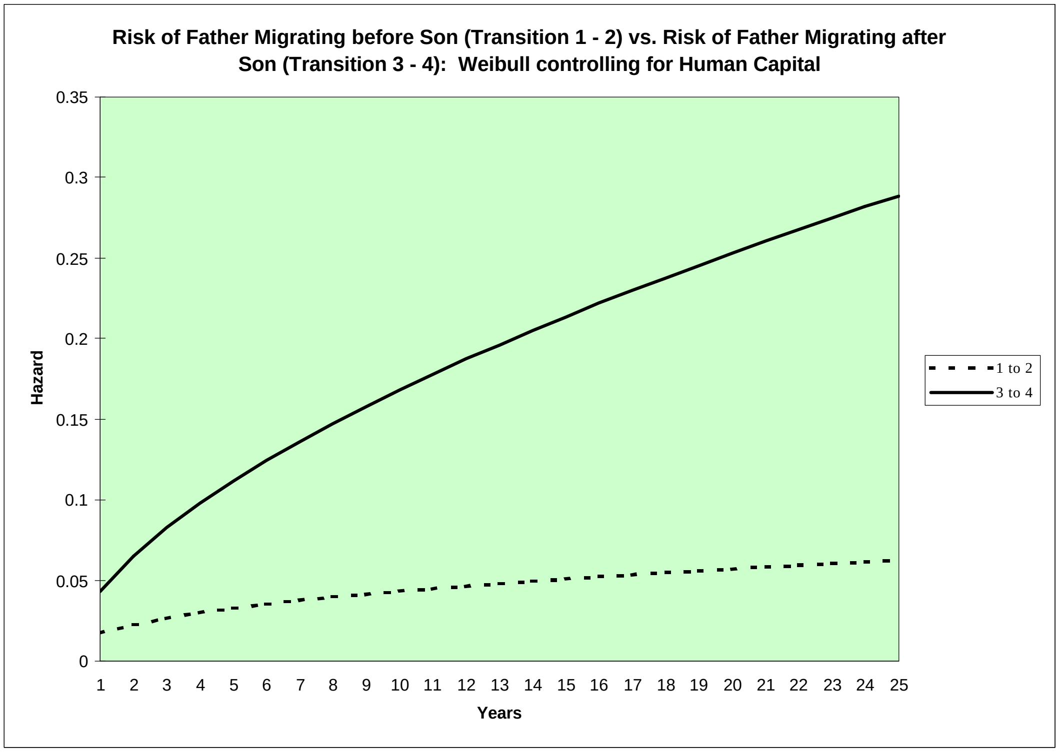


Figure 5) **Human Capital Model**



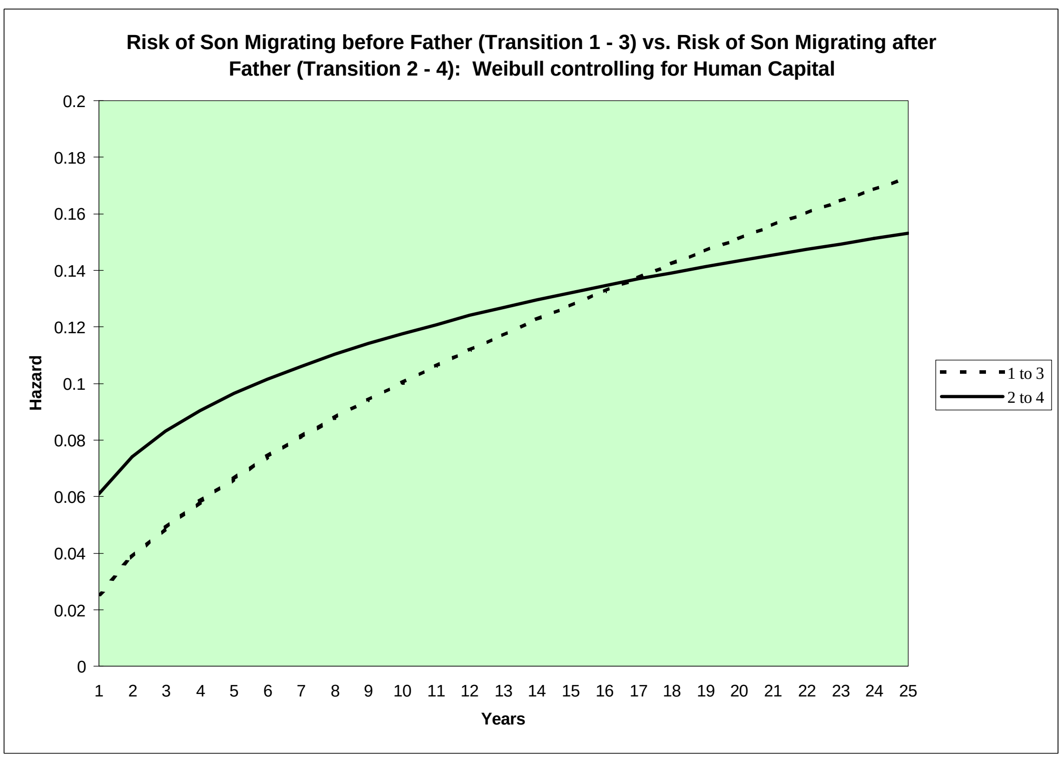
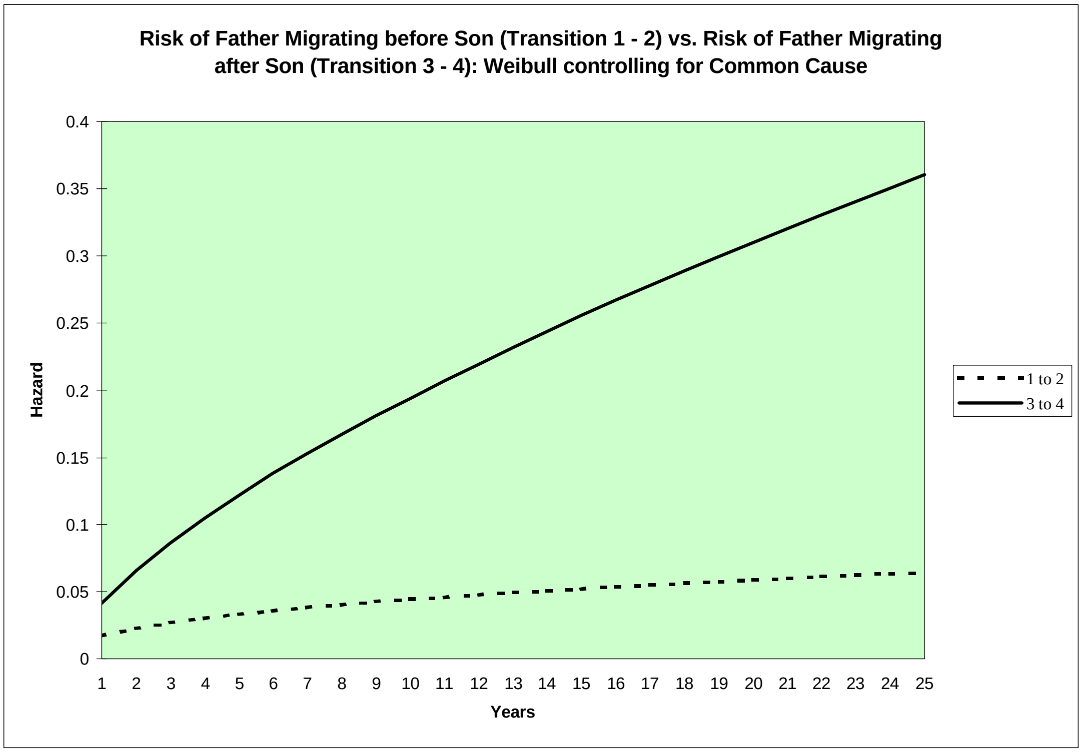


Figure 6) **Common Cause Model**



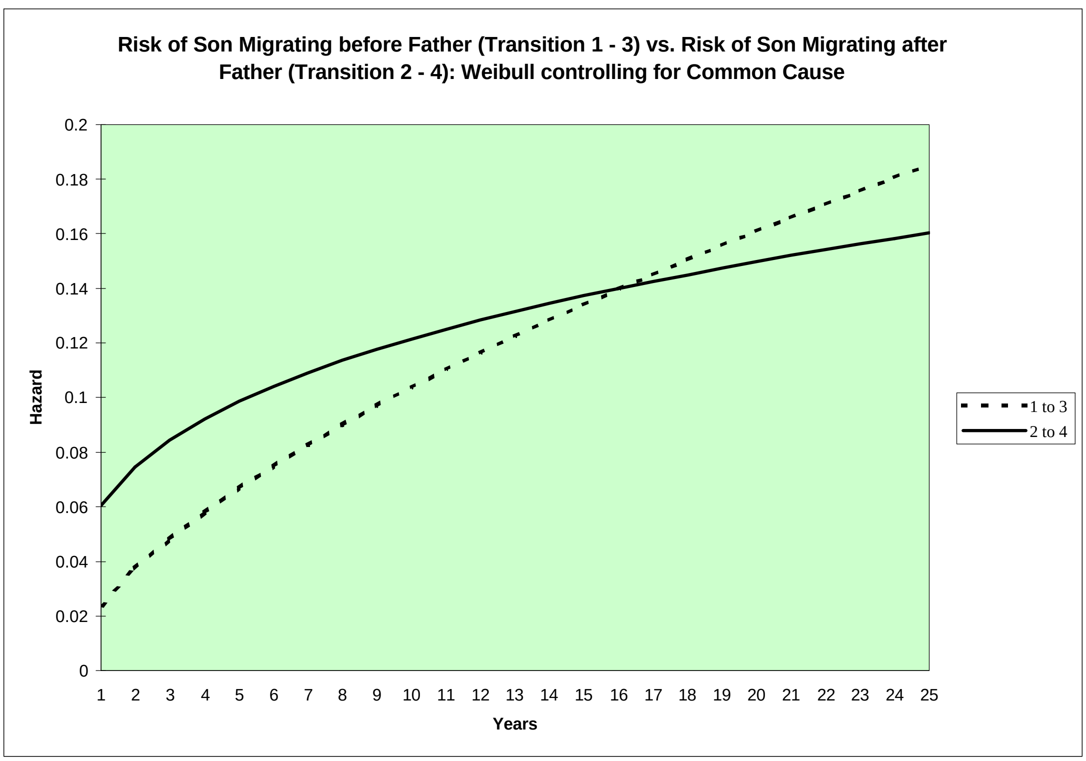
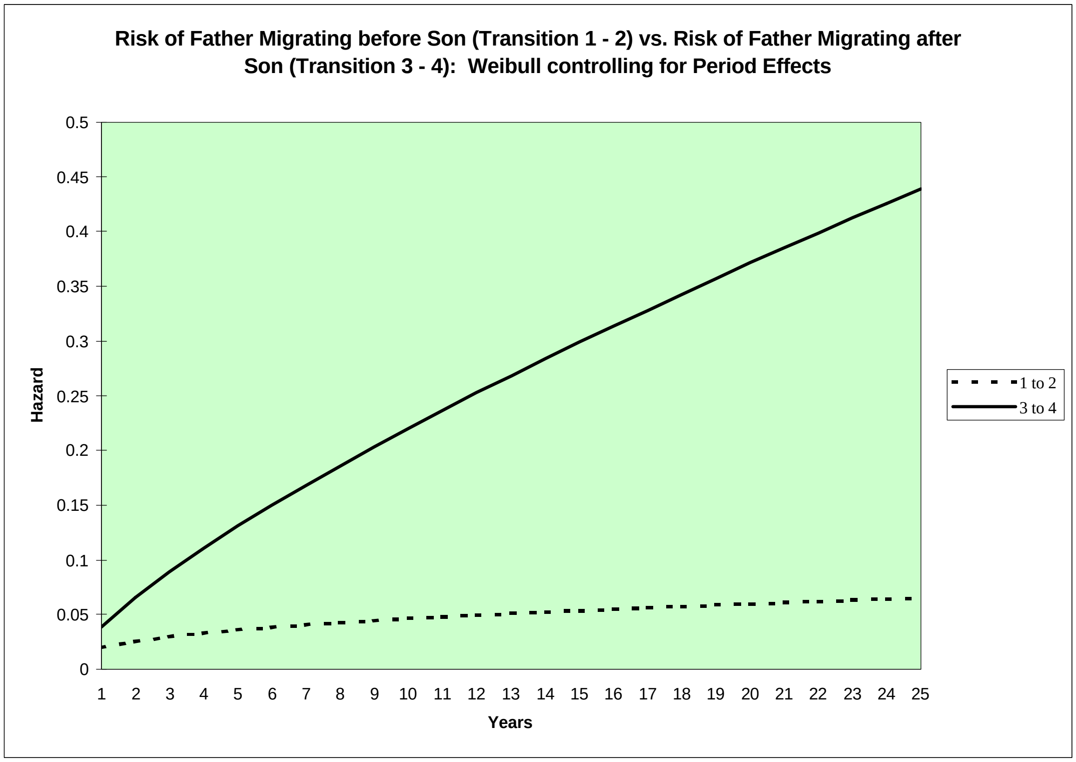


Figure 7) **Period Effect Model**



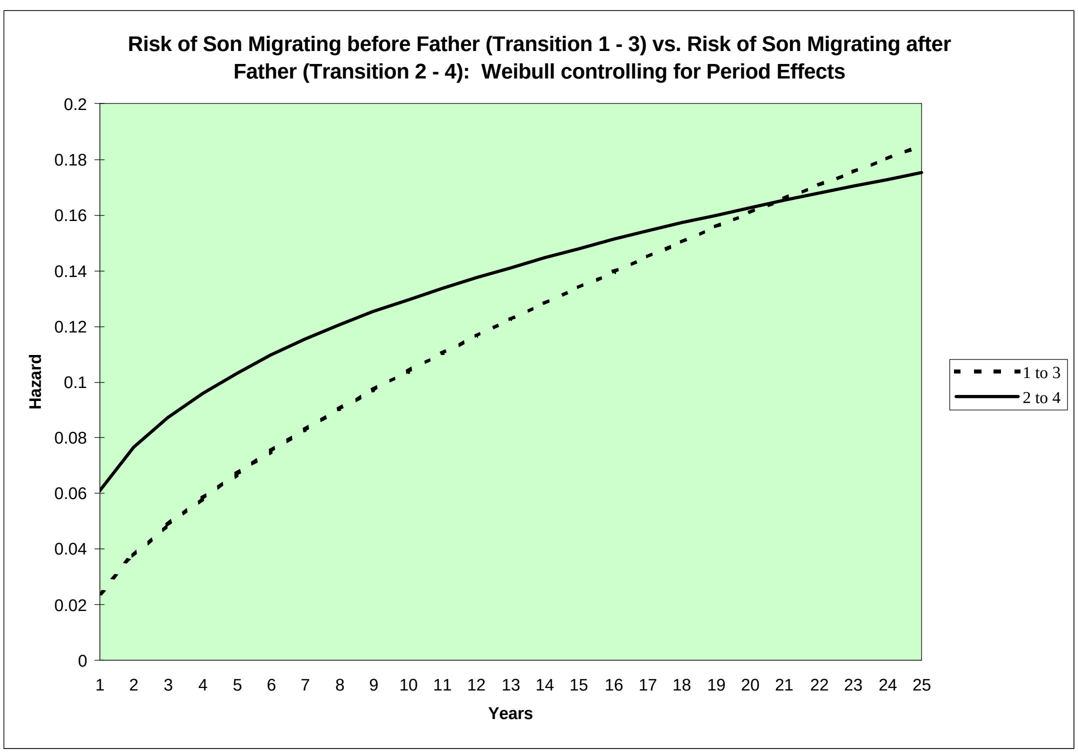
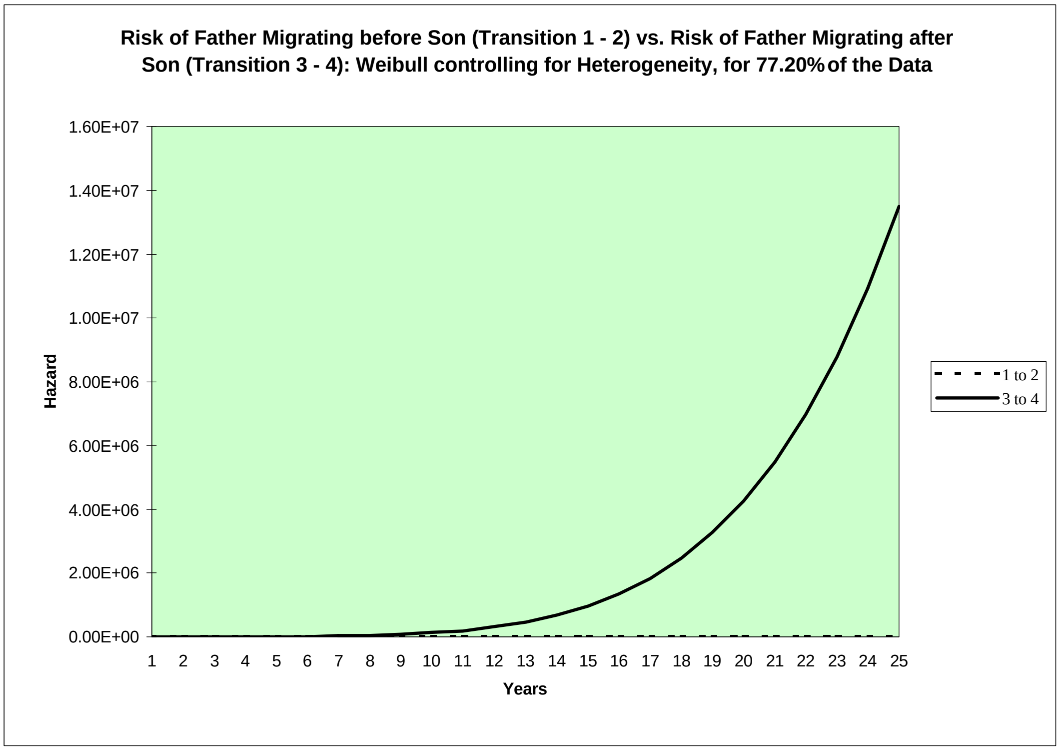


Figure 8) **Heterogeneity Model for 77.20% of the Data**



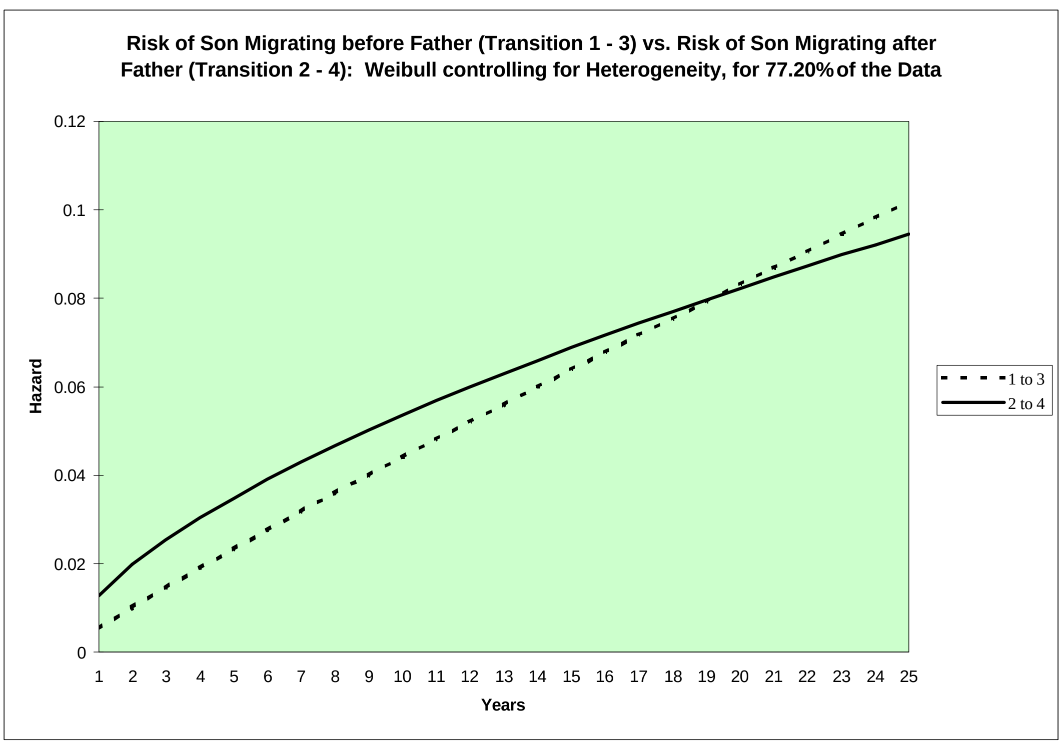
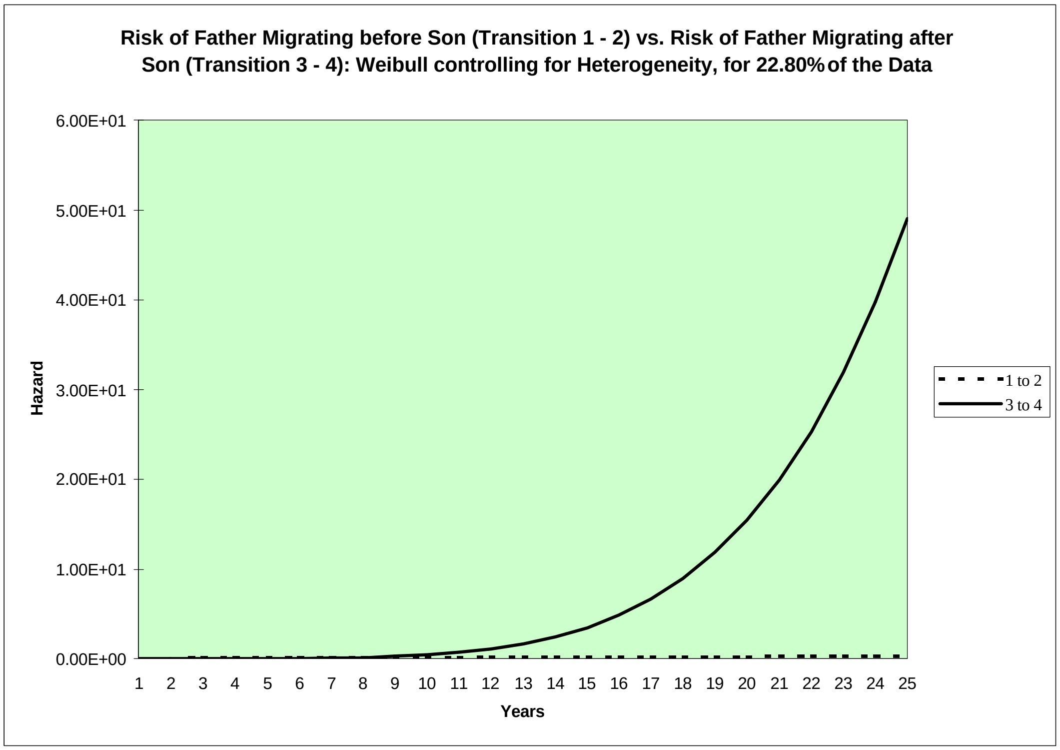


Figure 9) **Heterogeneity Model for 22.80% of the Data**



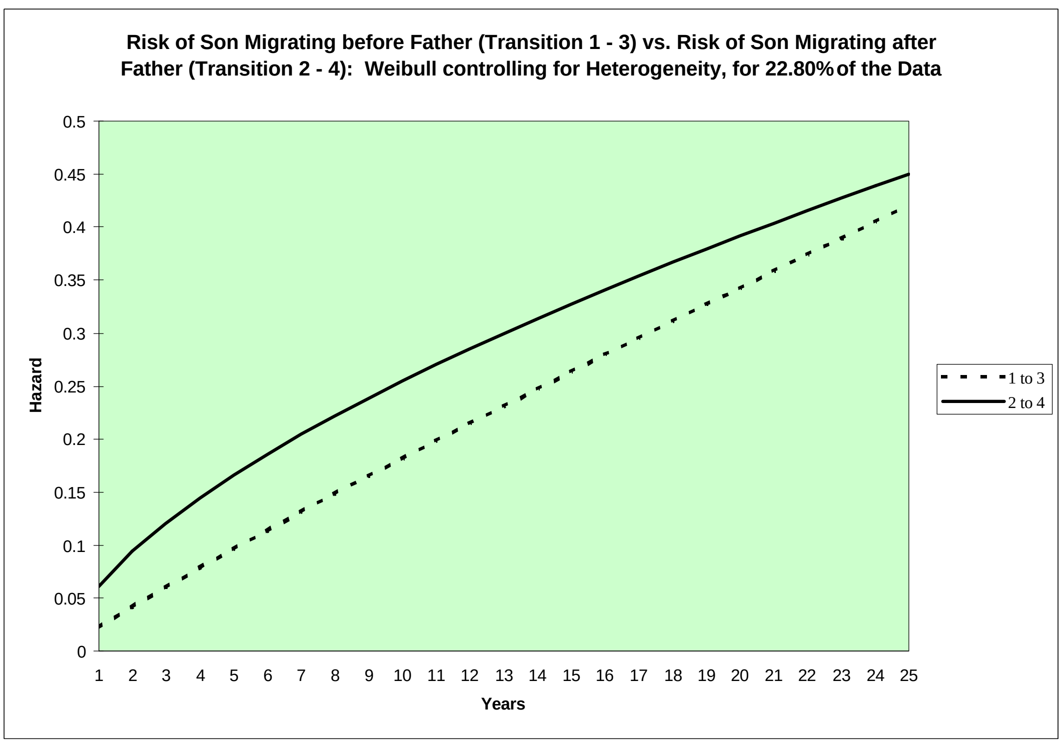


Table 11)

Life Table for Transition 1 - 2

t	q_x	l_x	d_x	L_x	T_x	E_x
0-1	0.02	100,000	1,941	99,029	1,559,055	15.74
1-2	0.03	98,059	2,469	96,824	1,460,026	15.08
2-3	0.03	95,590	2,802	94,189	1,363,201	14.47
3-4	0.03	92,788	3,030	91,273	1,269,012	13.90
4-5	0.04	89,758	3,187	88,164	1,177,739	13.36
5-6	0.04	86,571	3,292	84,925	1,089,575	12.83
6-7	0.04	83,279	3,355	81,601	1,004,650	12.31
7-8	0.04	79,924	3,385	78,231	923,049	11.80
8-9	0.04	76,539	3,388	74,844	844,818	11.29
9-10	0.05	73,150	3,369	71,466	769,973	10.77
10-11	0.05	69,781	3,331	68,116	698,508	10.25
11-12	0.05	66,450	3,277	64,812	630,392	9.73
12-13	0.05	63,173	3,211	61,568	565,580	9.19
13-14	0.05	59,963	3,133	58,396	504,013	8.63
14-15	0.05	56,829	3,047	55,305	445,617	8.06
15-16	0.05	53,782	2,955	52,304	390,311	7.46
16-17	0.06	50,827	2,857	49,399	338,007	6.84
17-18	0.06	47,970	2,755	46,593	288,608	6.19
18-19	0.06	45,216	2,650	43,891	242,015	5.51
19-20	0.06	42,566	2,543	41,295	198,124	4.80
20-21	0.06	40,023	2,435	38,806	156,830	4.04
21-22	0.06	37,588	2,327	36,425	118,024	3.24
22-23	0.06	35,261	2,220	34,151	81,599	2.39
23-24	0.06	33,041	2,114	31,984	47,448	1.48
24-25	0.06	30,928	2,009	15,464	15,464	1.00

Life Table for Transition 3 - 4

t	q_x	l_x	d_x	L_x	T_x	E_x
0-1	0.04	100,000	3,881	98,060	701,052	7.15
1-2	0.07	96,119	6,289	92,974	602,993	6.49
2-3	0.09	89,830	7,979	85,840	510,018	5.94
3-4	0.11	81,851	9,030	77,336	424,178	5.48
4-5	0.13	72,820	9,506	68,068	346,842	5.10
5-6	0.15	63,315	9,482	58,574	278,774	4.76
6-7	0.17	53,833	9,055	49,305	220,201	4.47
7-8	0.19	44,777	8,330	40,613	170,895	4.21
8-9	0.20	36,448	7,410	32,743	130,283	3.98
9-10	0.22	29,038	6,391	25,843	97,540	3.77
10-11	0.24	22,647	5,356	19,969	71,697	3.59
11-12	0.25	17,291	4,366	15,108	51,728	3.42
12-13	0.27	12,925	3,467	11,192	36,620	3.27
13-14	0.28	9,458	2,683	8,117	25,428	3.13
14-15	0.30	6,776	2,024	5,764	17,311	3.00
15-16	0.31	4,751	1,490	4,006	11,547	2.88
16-17	0.33	3,261	1,071	2,726	7,541	2.77
17-18	0.34	2,190	751	1,815	4,815	2.65
18-19	0.36	1,440	514	1,183	3,000	2.54
19-20	0.37	926	344	754	1,817	2.41
20-21	0.38	582	224	470	1,064	2.26
21-22	0.40	358	143	287	593	2.07
22-23	0.41	215	89	171	307	1.80
23-24	0.43	127	54	100	136	1.36
24-25	0.44	73	32	36	36	1.00

Table 12)

Life Table for Transition 1 - 3

t	q_x	l_x	d_x	L_x	T_x	E_x
0-1	0.02	100,000	2,430	98,785	1,078,077	10.91
1-2	0.04	97,570	3,672	95,734	979,292	10.23
2-3	0.05	93,898	4,563	91,617	883,559	9.64
3-4	0.06	89,335	5,205	86,733	791,942	9.13
4-5	0.07	84,131	5,642	81,310	705,209	8.67
5-6	0.08	78,489	5,905	75,536	623,900	8.26
6-7	0.08	72,584	6,018	69,574	548,364	7.88
7-8	0.09	66,565	6,004	63,563	478,789	7.53
8-9	0.10	60,561	5,884	57,619	415,226	7.21
9-10	0.10	54,678	5,677	51,839	357,606	6.90
10-11	0.11	49,000	5,403	46,299	305,767	6.60
11-12	0.12	43,598	5,078	41,059	259,468	6.32
12-13	0.12	38,519	4,719	36,160	218,410	6.04
13-14	0.13	33,800	4,339	31,631	182,250	5.76
14-15	0.13	29,462	3,950	27,486	150,619	5.48
15-16	0.14	25,511	3,563	23,730	123,132	5.19
16-17	0.15	21,949	3,185	20,356	99,402	4.88
17-18	0.15	18,764	2,822	17,353	79,046	4.56
18-19	0.16	15,942	2,481	14,701	61,693	4.20
19-20	0.16	13,461	2,164	12,379	46,992	3.80
20-21	0.17	11,297	1,873	10,361	34,613	3.34
21-22	0.17	9,424	1,609	8,620	24,252	2.81
22-23	0.18	7,815	1,372	7,129	15,632	2.19
23-24	0.18	6,443	1,162	5,862	8,503	1.45
24-25	0.19	5,281	977	2,641	2,641	1.00

Life Table for Transition 2 - 4

t	q_x	l_x	d_x	L_x	T_x	E_x
0-1	0.06	100,000	6,087	96,956	847,832	8.74
1-2	0.08	93,913	7,177	90,324	750,875	8.31
2-3	0.09	86,736	7,572	82,950	660,551	7.96
3-4	0.10	79,164	7,595	75,367	577,601	7.66
4-5	0.10	71,570	7,388	67,876	502,234	7.40
5-6	0.11	64,182	7,034	60,665	434,358	7.16
6-7	0.12	57,148	6,588	53,854	373,693	6.94
7-8	0.12	50,560	6,090	47,515	319,839	6.73
8-9	0.13	44,470	5,567	41,687	272,324	6.53
9-10	0.13	38,903	5,042	36,382	230,637	6.34
10-11	0.13	33,862	4,528	31,598	194,255	6.15
11-12	0.14	29,334	4,036	27,316	162,657	5.95
12-13	0.14	25,298	3,573	23,511	135,341	5.76
13-14	0.14	21,725	3,144	20,153	111,830	5.55
14-15	0.15	18,581	2,751	17,205	91,677	5.33
15-16	0.15	15,830	2,394	14,633	74,472	5.09
16-17	0.15	13,436	2,072	12,400	59,839	4.83
17-18	0.16	11,364	1,786	10,471	47,438	4.53
18-19	0.16	9,578	1,532	8,812	36,967	4.20
19-20	0.16	8,046	1,309	7,391	28,155	3.81
20-21	0.17	6,737	1,114	6,180	20,764	3.36
21-22	0.17	5,623	944	5,151	14,584	2.83
22-23	0.17	4,679	797	4,281	9,433	2.20
23-24	0.17	3,882	671	3,547	5,153	1.45
24-25	0.18	3,212	562	1,606	1,606	1.00

Appendix D

Table 13)

Descriptive Information By Community For All Transitions

	Guanajuato		Jalisco		Michoacan		Nayarit		Zacateca		Guerrero		San Luis Potosi		Colima		Total	
Survey Year																		
1982	0	0%	240	35%	90	14%	0	0%	0	0%	0	0%	0	0%	0	0%	330	11%
1983	0	0%	1	0%	1	0%	0	0%	0	0%	0	0%	0	0%	0	0%	2	0%
1987	202	29%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	202	7%
1988	172	24%	242	36%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	414	14%
1989	0	0%	1	0%	147	24%	0	0%	0	0%	0	0%	0	0%	0	0%	148	5%
1990	70	10%	0	0%	173	28%	130	100%	0	0%	0	0%	0	0%	0	0%	373	12%
1991	86	12%	79	12%	134	22%	0	0%	236	57%	0	0%	0	0%	0	0%	535	18%
1992	176	25%	117	17%	75	12%	0	0%	0	0%	0	0%	0	0%	0	0%	368	12%
1993	0	0%	0	0%	2	0%	0	0%	0	0%	36	100%	105	29%	0	0%	143	5%
1994	0	0%	0	0%	0	0%	0	0%	177	43%	0	0%	259	71%	85	100%	521	17%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Father's Occupation																		
Unemployed	78	11%	96	14%	72	12%	12	9%	76	18%	0	0%	80	22%	15	18%	429	14%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	228	32%	169	25%	276	44%	67	52%	67	16%	6	17%	99	27%	23	27%	935	31%
Skilled	400	57%	415	61%	274	44%	51	39%	270	65%	30	83%	185	51%	47	55%	1,672	55%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Son's Occupation																		
Unemployed	25	4%	20	3%	24	4%	4	3%	11	3%	0	0%	23	6%	3	4%	110	4%
Student	92	13%	83	12%	72	12%	10	8%	55	13%	13	36%	46	13%	11	13%	382	13%
Unskilled	208	29%	234	34%	300	48%	73	56%	148	36%	7	19%	127	35%	29	34%	1,126	37%
Skilled	381	54%	343	50%	226	36%	43	33%	199	48%	16	44%	168	46%	42	49%	1,418	47%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Father's Education																		
0 to 3 years	426	60%	463	68%	440	71%	92	71%	257	62%	3	8%	169	46%	53	62%	1,903	63%
4 to 9 years	245	35%	192	28%	158	25%	35	27%	110	27%	26	72%	151	41%	29	34%	946	31%
10+ years	35	5%	25	4%	24	4%	3	2%	46	11%	7	19%	44	12%	3	4%	187	6%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Son's Education																		
0 to 3 years	104	15%	127	19%	145	23%	21	16%	65	16%	1	3%	42	12%	11	13%	516	17%
4 to 9 years	437	62%	404	59%	337	54%	69	53%	226	55%	15	42%	173	48%	43	51%	1,704	56%
10+ years	165	23%	149	22%	140	23%	40	31%	122	30%	20	56%	149	41%	31	36%	816	27%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Father's Documentation																		
Undocumented	132	19%	163	24%	198	32%	35	27%	115	28%	9	25%	108	30%	23	27%	783	26%
Documented	574	81%	517	76%	424	68%	95	73%	298	72%	27	75%	256	70%	62	73%	2,253	74%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%
Son's Documentation																		
Undocumented	108	15%	188	28%	189	30%	41	32%	154	37%	6	17%	102	28%	19	22%	807	27%
Documented	598	85%	492	72%	433	70%	89	68%	259	63%	30	83%	262	72%	66	78%	2,229	73%
	706	100%	680	100%	622	100%	130	100%	413	100%	36	100%	364	100%	85	100%	3,036	100%

Table 14)

Descriptive Information By Community For Transition 1 to 2

	Guanajuato		Jalisco		Michoacan		Nayarit		Zacateca		Guerrero		San Luis Potosi		Colima		Total	
Survey Year																		
1982	0	0%	8	33%	2	8%	0	0%	0	0%	0	0%	0	0%	0	0%	10	8%
1983	0	0%	0	0%	1	4%	0	0%	0	0%	0	0%	0	0%	0	0%	1	1%
1987	9	28%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	9	8%
1988	6	19%	7	29%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	13	11%
1989	0	0%	0	0%	4	16%	0	0%	0	0%	0	0%	0	0%	0	0%	4	3%
1990	1	3%	0	0%	7	28%	7	100%	0	0%	0	0%	0	0%	0	0%	15	13%
1991	4	13%	2	8%	9	36%	0	0%	7	58%	0	0%	0	0%	0	0%	22	19%
1992	12	38%	7	29%	2	8%	0	0%	0	0%	0	0%	0	0%	0	0%	21	18%
1993	0	0%	0	0%	0	0%	0	0%	0	0%	1	100%	2	13%	0	0%	3	3%
1994	0	0%	0	0%	0	0%	0	0%	5	42%	0	0%	13	87%	2	100%	20	17%
	32	100%	24	100%	25	100%	7	100%	12	100%	1	100%	15	100%	2	100%	118	100%
Occupation																		
Unemployed	5	16%	5	21%	5	20%	3	43%	4	33%	0	0%	3	20%	0	0%	25	21%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	11	34%	5	21%	10	40%	3	43%	1	8%	1	100%	7	47%	1	50%	39	33%
Skilled	16	50%	14	58%	10	40%	1	14%	7	58%	0	0%	5	33%	1	50%	54	46%
	32	100%	24	100%	25	100%	7	100%	12	100%	1	100%	15	100%	2	100%	118	100%
Education																		
0 to 3 years	18	56%	20	83%	20	80%	5	71%	10	83%	0	0%	7	47%	1	50%	81	69%
4 to 9 years	13	41%	2	8%	5	20%	2	29%	0	0%	1	100%	7	47%	1	50%	31	26%
10+ years	1	3%	2	8%	0	0%	0	0%	2	17%	0	0%	1	7%	0	0%	6	5%
	32	100%	24	100%	25	100%	7	100%	12	100%	1	100%	15	100%	2	100%	118	100%
Documentation																		
Undocumented	23	72%	18	75%	18	72%	6	86%	9	75%	1	100%	11	73%	2	100%	88	75%
Documented	9	28%	6	25%	7	28%	1	14%	3	25%	0	0%	4	27%	0	0%	30	25%
	32	100%	24	100%	25	100%	7	100%	12	100%	1	100%	15	100%	2	100%	118	100%

Table 15)

Descriptive Information By Community For Transition 1 to 3

	Guanajuato		Jalisco		Michoacan		Nayarit		Zacateca		Guerrero		San Luis Potosi		Colima		Total	
Survey Year																		
1982	0	0%	22	28%	9	14%	0	0%	0	0%	0	0%	0	0%	0	0%	31	10%
1983	0	0%	1	1%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	1	0%
1987	16	33%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	16	5%
1988	11	22%	37	47%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	48	16%
1989	0	0%	0	0%	27	42%	0	0%	0	0%	0	0%	0	0%	0	0%	27	9%
1990	7	14%	0	0%	15	23%	24	100%	0	0%	0	0%	0	0%	0	0%	46	15%
1991	1	2%	4	5%	7	11%	0	0%	24	63%	0	0%	0	0%	0	0%	36	12%
1992	14	29%	15	19%	5	8%	0	0%	0	0%	0	0%	0	0%	0	0%	34	11%
1993	0	0%	0	0%	1	2%	0	0%	0	0%	3	100%	4	11%	0	0%	8	3%
1994	0	0%	0	0%	0	0%	0	0%	14	37%	0	0%	34	89%	13	100%	61	20%
	49	100%	79	100%	64	100%	24	100%	38	100%	3	100%	38	100%	13	100%	308	100%
Occupation																		
Unemployed	1	2%	4	5%	1	2%	2	8%	1	3%	0	0%	1	3%	0	0%	10	3%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	24	49%	37	47%	43	67%	17	71%	17	45%	2	67%	21	55%	7	54%	168	55%
Skilled	24	49%	38	48%	20	31%	5	21%	20	53%	1	33%	16	42%	6	46%	130	42%
	49	100%	79	100%	64	100%	24	100%	38	100%	3	100%	38	100%	13	100%	308	100%
Education																		
0 to 3 years	5	10%	23	29%	23	36%	5	21%	15	39%	0	0%	9	24%	2	15%	82	27%
4 to 9 years	40	82%	52	66%	33	52%	15	63%	19	50%	2	67%	19	50%	8	62%	188	61%
10+ years	4	8%	4	5%	8	13%	4	17%	4	11%	1	33%	10	26%	3	23%	38	12%
	49	100%	79	100%	64	100%	24	100%	38	100%	3	100%	38	100%	13	100%	308	100%
Documentation																		
Undocumented	45	92%	71	90%	57	89%	24	100%	30	79%	3	100%	33	87%	11	85%	274	89%
Documented	4	8%	8	10%	7	11%	0	0%	8	21%	0	0%	5	13%	2	15%	34	11%
	49	100%	79	100%	64	100%	24	100%	38	100%	3	100%	38	100%	13	100%	308	100%

Table 16)

Descriptive Information By Community For Transition 2 to 4

	Guanajuato		Jalisco		Michoacan		Nayarit		Zacateca		Guerrero		San Luis Potosi		Colima		Total	
Survey Year																		
1982	0	0%	27	21%	26	17%	0	0%	0	0%	0	0%	0	0%	0	0%	53	9%
1983	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
1987	17	25%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	17	3%
1988	5	7%	73	57%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	78	13%
1989	0	0%	1	1%	44	29%	0	0%	0	0%	0	0%	0	0%	0	0%	45	7%
1990	23	34%	0	0%	64	42%	24	100%	0	0%	0	0%	0	0%	0	0%	111	18%
1991	1	1%	20	16%	10	7%	0	0%	118	80%	0	0%	0	0%	0	0%	149	25%
1992	21	31%	7	5%	6	4%	0	0%	0	0%	0	0%	0	0%	0	0%	34	6%
1993	0	0%	0	0%	1	1%	0	0%	0	0%	3	100%	1	1%	0	0%	5	1%
1994	0	0%	0	0%	0	0%	0	0%	30	20%	0	0%	77	99%	7	100%	114	19%
	67	100%	128	100%	151	100%	24	100%	148	100%	3	100%	78	100%	7	100%	606	100%
Occupation																		
Unemployed	3	4%	2	2%	3	2%	0	0%	2	1%	0	0%	7	9%	1	14%	18	3%
Student	0	0%	2	2%	1	1%	1	4%	0	0%	0	0%	0	0%	0	0%	4	1%
Unskilled	44	66%	75	59%	114	75%	17	71%	83	56%	0	0%	37	47%	3	43%	373	62%
Skilled	20	30%	49	38%	33	22%	6	25%	63	43%	3	100%	34	44%	3	43%	211	35%
	67	100%	128	100%	151	100%	24	100%	148	100%	3	100%	78	100%	7	100%	606	100%
Education																		
0 to 3 years	10	15%	30	23%	57	38%	4	17%	31	21%	0	0%	5	6%	2	29%	139	23%
4 to 9 years	49	73%	76	59%	80	53%	13	54%	97	66%	2	67%	59	76%	2	29%	378	62%
10+ years	8	12%	22	17%	14	9%	7	29%	20	14%	1	33%	14	18%	3	43%	89	15%
	67	100%	128	100%	151	100%	24	100%	148	100%	3	100%	78	100%	7	100%	606	100%
Documentation																		
Undocumented	61	91%	112	88%	126	83%	17	71%	123	83%	3	100%	66	85%	7	100%	515	85%
Documented	6	9%	16	13%	25	17%	7	29%	25	17%	0	0%	12	15%	0	0%	91	15%
	67	100%	128	100%	151	100%	24	100%	148	100%	3	100%	78	100%	7	100%	606	100%

Table 17)

Descriptive Information By Community For Transition 3 to 4

	Guanajuato		Jalisco		Michoacan		Nayarit		Zacateca		Guerrero		San Luis Potosi		Colima		Total	
Survey Year																		
1982	0	0%	0	0%	1	33%	0	0%	0	0%	0	0%	0	0%	0	0%	1	5%
1983	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
1987	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
1988	1	50%	4	67%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	5	24%
1989	0	0%	0	0%	1	33%	0	0%	0	0%	0	0%	0	0%	0	0%	1	5%
1990	0	0%	0	0%	1	33%	3	100%	0	0%	0	0%	0	0%	0	0%	4	19%
1991	0	0%	0	0%	0	0%	0	0%	3	75%	0	0%	0	0%	0	0%	3	14%
1992	1	50%	2	33%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	3	14%
1993	0	0%	0	0%	0	0%	0	0%	0	0%	1	100%	0	0%	0	0%	1	5%
1994	0	0%	0	0%	0	0%	0	0%	1	25%	0	0%	1	100%	1	100%	3	14%
	2	100%	6	100%	3	100%	3	100%	4	100%	1	100%	1	100%	1	100%	21	100%
Occupation																		
Unemployed	0	0%	1	17%	1	33%	0	0%	1	25%	0	0%	0	0%	0	0%	3	14%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	1	50%	3	50%	1	33%	2	67%	0	0%	0	0%	0	0%	1	100%	8	38%
Skilled	1	50%	2	33%	1	33%	1	33%	3	75%	1	100%	1	100%	0	0%	10	48%
	2	100%	6	100%	3	100%	3	100%	4	100%	1	100%	1	100%	1	100%	21	100%
Education																		
0 to 3 years	2	100%	6	100%	3	100%	2	67%	4	100%	0	0%	0	0%	1	100%	18	86%
4 to 9 years	0	0%	0	0%	0	0%	1	33%	0	0%	1	100%	1	100%	0	0%	3	14%
10+ years	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
	2	100%	6	100%	3	100%	3	100%	4	100%	1	100%	1	100%	1	100%	21	100%
Documentation																		
Undocumented	1	50%	5	83%	2	67%	3	100%	2	50%	1	100%	1	100%	1	100%	16	76%
Documented	1	50%	1	17%	1	33%	0	0%	2	50%	0	0%	0	0%	0	0%	5	24%
	2	100%	6	100%	3	100%	3	100%	4	100%	1	100%	1	100%	1	100%	21	100%

Table 18)

Descriptive Information By Survey Year for All Transitions

	1982		1983		1987		1988		1989		1990		1991		1992		1993	
Father's Occupation																		
Unemployed	39	12%	0	0%	7	3%	40	10%	15	10%	33	9%	121	23%	63	17%	47	33%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	64	19%	1	50%	63	31%	161	39%	76	51%	185	50%	125	23%	106	29%	16	11%
Skilled	227	69%	1	50%	132	65%	213	51%	57	39%	155	42%	289	54%	199	54%	80	56%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%
Son's Occupation																		
Unemployed	9	3%	0	0%	5	2%	10	2%	6	4%	11	3%	20	4%	21	6%	4	3%
Student	44	13%	0	0%	20	10%	29	7%	14	9%	39	10%	71	13%	61	17%	35	24%
Unskilled	88	27%	0	0%	53	26%	171	41%	84	57%	175	47%	224	42%	122	33%	23	16%
Skilled	189	57%	2	100%	124	61%	204	49%	44	30%	148	40%	220	41%	164	45%	81	57%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%
Father's Education																		
0 to 3 years	224	68%	2	100%	151	75%	293	71%	110	74%	273	73%	327	61%	219	60%	16	11%
4 to 9 years	103	31%	0	0%	49	24%	105	25%	35	24%	91	24%	171	32%	118	32%	84	59%
10+ years	3	1%	0	0%	2	1%	16	4%	3	2%	9	2%	37	7%	31	8%	43	30%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%
Son's Education																		
0 to 3 years	60	18%	1	50%	37	18%	101	24%	39	26%	84	23%	77	14%	50	14%	4	3%
4 to 9 years	220	67%	1	50%	149	74%	243	59%	81	55%	189	51%	295	55%	196	53%	40	28%
10+ years	50	15%	0	0%	16	8%	70	17%	28	19%	100	27%	163	30%	122	33%	99	69%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%
Father's Documentation																		
Undocumented	85	26%	1	50%	29	14%	93	22%	52	35%	128	34%	139	26%	77	21%	23	16%
Documented	245	74%	1	50%	173	86%	321	78%	96	65%	245	66%	396	74%	291	79%	120	84%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%
Son's Documentation																		
Undocumented	77	23%	0	0%	31	15%	117	28%	70	47%	128	34%	156	29%	61	17%	10	7%
Documented	253	77%	2	100%	171	85%	297	72%	78	53%	245	66%	379	71%	307	83%	133	93%
	330	100%	2	100%	202	100%	414	100%	148	100%	373	100%	535	100%	368	100%	143	100%

Table 19)

Descriptive Information By Survey Year for Transition 1 to 2

	1982		1983		1987		1988		1989	
Occupation										
Unemployed	1	10%	0	0%	1	11%	2	15%	1	25%
Student	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	1	10%	1	100%	4	44%	5	38%	1	25%
Skilled	8	80%	0	0%	4	44%	6	46%	2	50%
	10	100%	1	100%	9	100%	13	100%	4	100%
Education										
0 to 3 years	8	80%	1	100%	6	67%	10	77%	3	75%
4 to 9 years	1	10%	0	0%	3	33%	3	23%	1	25%
10+ years	1	10%	0	0%	0	0%	0	0%	0	0%
	10	100%	1	100%	9	100%	13	100%	4	100%
Documentation										
Undocumented	5	50%	1	100%	6	67%	9	69%	2	50%
Documented	5	50%	0	0%	3	33%	4	31%	2	50%
	10	100%	1	100%	9	100%	13	100%	4	100%

	1990		1991		1992		1993	
Occupation								
Unemployed	6	40%	6	27%	5	24%	1	33%
Student	0	0%	0	0%	0	0%	0	0%
Unskilled	7	47%	7	32%	4	19%	1	33%
Skilled	2	13%	9	41%	12	57%	1	33%
	15	100%	22	100%	21	100%	3	100%
Education								
0 to 3 years	11	73%	18	82%	13	62%	1	33%
4 to 9 years	4	27%	3	14%	7	33%	2	67%
10+ years	0	0%	1	5%	1	5%	0	0%
	15	100%	22	100%	21	100%	3	100%
Documentation								
Undocumented	12	80%	16	73%	18	86%	2	67%
Documented	3	20%	6	27%	3	14%	1	33%
	15	100%	22	100%	21	100%	3	100%

Table 20)

Descriptive Information By Survey Year for Transition 1 to 3

	1982		1983		1987		1988		1989		1990		1991		1992		1993	
Occupation																		
Unemployed	1	3%	0	0%	0	0%	1	2%	0	0%	2	4%	1	3%	4	12%	0	0%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	15	48%	0	0%	6	38%	25	52%	21	78%	27	59%	19	53%	17	50%	5	63%
Skilled	15	48%	1	100%	10	63%	22	46%	6	22%	17	37%	16	44%	13	38%	3	38%
	31	100%	1	100%	16	100%	48	100%	27	100%	46	100%	36	100%	34	100%	8	100%
Education																		
0 to 3 years	12	39%	0	0%	2	13%	15	31%	10	37%	11	24%	13	36%	4	12%	0	0%
4 to 9 years	19	61%	1	100%	13	81%	31	65%	13	48%	28	61%	20	56%	26	76%	4	50%
10+ years	0	0%	0	0%	1	6%	2	4%	4	15%	7	15%	3	8%	4	12%	4	50%
	31	100%	1	100%	16	100%	48	100%	27	100%	46	100%	36	100%	34	100%	8	100%
Documentation																		
Undocumented	28	90%	0	0%	14	88%	46	96%	26	96%	42	91%	30	83%	29	85%	6	75%
Documented	3	10%	1	100%	2	13%	2	4%	1	4%	4	9%	6	17%	5	15%	2	25%
	31	100%	1	100%	16	100%	48	100%	27	100%	46	100%	36	100%	34	100%	8	100%

Table 21)

Descriptive Information By Survey Year for Transition 2 to 4

	1982		1983		1987		1988		1989		1990		1991		1992		1993	
Occupation																		
Unemployed	0	0%	0	0%	0	0%	2	3%	2	4%	2	2%	2	1%	2	6%	0	0%
Student	0	0%	0	0%	0	0%	1	1%	0	0%	2	2%	1	1%	0	0%	0	0%
Unskilled	31	58%	0	0%	13	76%	45	58%	33	73%	83	75%	90	60%	23	68%	1	20%
Skilled	22	42%	0	0%	4	24%	30	38%	10	22%	24	22%	56	38%	9	26%	4	80%
	53	100%	0	0%	17	100%	78	100%	45	100%	111	100%	149	100%	34	100%	5	100%
Education																		
0 to 3 years	11	21%	0	0%	4	24%	23	29%	14	31%	40	36%	32	21%	4	12%	0	0%
4 to 9 years	37	70%	0	0%	13	76%	46	59%	27	60%	54	49%	94	63%	22	65%	4	80%
10+ years	5	9%	0	0%	0	0%	9	12%	4	9%	17	15%	23	15%	8	24%	1	20%
	53	100%	0	0%	17	100%	78	100%	45	100%	111	100%	149	100%	34	100%	5	100%
Documentation																		
Undocumented	47	89%	0	0%	17	100%	68	87%	41	91%	86	77%	123	83%	29	85%	4	80%
Documented	6	11%	0	0%	0	0%	10	13%	4	9%	25	23%	26	17%	5	15%	1	20%
	53	100%	0	0%	17	100%	78	100%	45	100%	111	100%	149	100%	34	100%	5	100%

Table 22)

Descriptive Information By Survey Year for Transition 3 to 4

	1982		1983		1987		1988		1989		1990		1991		1992		1993	
Occupation																		
Unemployed	1	100%	0	0%	0	0%	1	20%	0	0%	0	0%	1	33%	0	0%	0	0%
Student	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Unskilled	0	0%	0	0%	0	0%	3	60%	0	0%	3	75%	0	0%	1	33%	0	0%
Skilled	0	0%	0	0%	0	0%	1	20%	1	100%	1	25%	2	67%	2	67%	1	100%
	1	100%	0	0%	0	0%	5	100%	1	100%	4	100%	3	100%	3	100%	1	100%
Education																		
0 to 3 years	1	100%	0	0%	0	0%	5	100%	1	100%	3	75%	3	100%	3	100%	0	0%
4 to 9 years	0	0%	0	0%	0	0%	0	0%	0	0%	1	25%	0	0%	0	0%	1	100%
10+ years	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
	1	100%	0	0%	0	0%	5	100%	1	100%	4	100%	3	100%	3	100%	1	100%
Documentation																		
Undocumented	0	0%	0	0%	0	0%	4	80%	1	100%	4	100%	2	67%	2	67%	1	100%
Documented	1	100%	0	0%	0	0%	1	20%	0	0%	0	0%	1	33%	1	33%	0	0%
	1	100%	0	0%	0	0%	5	100%	1	100%	4	100%	3	100%	3	100%	1	100%

Appendix E
DOCUMENTATION OF DATA FILES

Mexican Migration Project
Introduction to Data
November 1996

University of Pennsylvania

The Mexican Migration Project was funded by the National Institute of Child Health and Human Development (Grant 1 R37 HD-24047) to create a comprehensive dataset on Mexican migration to the United States. Two to five Mexican communities were surveyed each year during December and January of successive years using simple random sampling methods. The sample size was generally 200 households unless the community was under 500 residents, in which case a smaller number of households was interviewed. If initial fieldwork indicated that U.S. migrants returned home in large numbers during months other than December or January, interviewers returned to the community during those months to gather a portion of the 200 interviews.

These representative community surveys yielded information on where migrants went in the United States, and during the months of July and August interviewers traveled to those U.S. destinations to gather non-random samples of 10 to 20 out-migrant households from each community. The U.S.-based samples thus contain migrants who have established their households in the United States.

As of November 1996, 39 communities have been sampled using these methods, the first during the winter of 1982-1983. The dataset contains 7,143 households interviewed in Mexico and 516 surveyed in the United States. The communities were chosen to provide a range of different sizes, regions, ethnic compositions, and economic bases. The sample thus includes isolated rural towns, large farming communities, small cities, and very large metropolitan areas; it covers communities in the states of Guanajuato, Michoacan, Jalisco, Nayarit, and Zacatecas; it contains both indigenous and mestizo towns; and it embraces communities that specialize in mining, fishing, farming, and manufacturing, as well as those that feature very diversified economies. Characteristics of the full sample are summarized in Table 1.

The study's questionnaire followed the logic of an ethnosurvey, which blends qualitative and quantitative data-gathering techniques. A semi-structured instrument required that identical information be obtained for each person, but question-wording and ordering were not fixed. The precise phrasing and timing of each query was left to the judgment of the interviewer, depending on circumstances. The design thereby combines features of ethnography and standard survey research.

The interview began by identifying the household head and systematically enumerating the spouse and children, beginning with the oldest. All children of the head were listed on the questionnaire whether or not they lived at home, but if a son or daughter was a member of another household, this fact was ascertained and recorded. A child was considered to be living in a separate household if he or she was married, maintained a separate house or kitchen, and organized expenses separately. After listing the head, spouse, and children, other household members were identified and their relationship to the head clarified. The ethnosurvey questionnaire proceeded in three phases, with the household head serving as the principal respondent for all persons in the sample. In the first phase, the interviewer gathered basic social and demographic information on the head, spouse, resident and non-resident children, and other household members, including age, birthplace, marital status, education, and occupation. The interviewer then asked which of those enumerated had ever been to the U.S. For those individuals with migrant experience the interviewer recorded the total number of U.S. trips, as well as information about the first and most recent U.S. trips, including the year, duration, destination, U.S. occupation, legal status, and hourly wage. This exercise was then repeated for first and most recent migrations within Mexico.

The second phase of the ethnosurvey questionnaire compiled a year-by-year life history for all household heads, including a childbearing history, a property history, a housing history, a business history, and a labor history. The third and final phase of the questionnaire gathered information about the household head's experiences on his or her most recent trip to the United States, including the mode of border-crossing, the kind and number of accompanying relatives, the kind and number of relatives already present in the United States, the number of social ties that had been formed with U.S. citizens, English language ability, job characteristics, and use of U.S. social services.

After the ethnosurvey questionnaires were completed, data were entered in Mexico using the SPSS Data Entry package in a DOS operating system. The entry programs performed initial screening, range checks, and simple tests for logical consistency. The preliminary files were then shipped to the University of Chicago or the University of Pennsylvania, where additional data cleaning was performed, numeric codes were assigned to occupations and places, and the final datasets were assembled. Four basic files were created, each corresponding to a different unit of analysis: PERSFILE, MIGFILE, HOUSFILE, and LIFEFILE.

PERSFILE contains information on all persons enumerated within sample households, including older sons and daughters of the household head who no longer reside at home. In order to make this file representative of the community, these non-resident children must be excluded by selecting on the household membership variable. HOUSEFILE contains information on each household enumerated in the sample. MIGFILE contains detailed data on the household head's most recent trip to the United States. LIFEFILE contains life histories constructed for all household heads, regardless of migrant status. The latter file follows each household head through life year-by-year, so that person-years represent the units of analysis.

Data at the community and municipio levels were also collected, using several sources. First, since 1990, interviewers have used a special community questionnaire to collect and compile data from various sources in each community. Next, data were compiled from the Anuario Estadistico of 1993, published in Mexico by INEGI. Finally, data were compiled from the published volumes of the Mexican censuses for 1930, 1940, 1950, 1960, 1970, 1980, and 1990. These decennial census data were then interpolated for years between the censuses and extrapolated for years after 1990 (see Appendix F for notes and details of variable construction, interpolation, and extrapolation). COMCROSS is a cross-sectional file that contains data on thirty communities for the period 1990-93, drawn from the community questionnaire, from the Anuarios Estadisticos, and from the Mexican censuses. COMYEAR is a longitudinal file that contains data for the same thirty communities, drawn from the Mexican censuses and from the community questionnaire, for each year from 1930 to 1993. The COMCROSS and COMYEAR files are available by request.

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