The Next Generation:
A New Approach to Explain Migration

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Introduction

In spite of many studies on international migration, our understanding of immigrant farmworkers in the United States (U.S.) is limited, and even less is known about children of immigrant farmworkers and their migration decisions and expectations. Specifically, there exists a gap in the knowledge about migration decisions after the first move from the origin to the new destination, and who decides to stay there, move back to the origin or move on to another destination. Most literature on sequential migration has focused on individual factors rather than household factors (Djajić, 2008) for international instead of internal migration, and has not included children of immigrants in their analyses. Basically, the debate has explored the return decision of highly educated migrants with less attention to unskilled migrants like farmworkers.

Literature on migration has explored two main streams: 1) causes or determinants driving internal and international movement processes, and 2) consequences or returns to migration. Economic factors arise as the main drivers to explain the migration phenomenon; the majority of studies explain the migration process as a response to labor market conditions – e.g. unemployment rate and wages (Galarza & Yancari, 2005). In the same line, studies about migration's consequences have focused mostly on economic factors as well, without a subjective approach.

Studies about the determinants of migration have explained the decision to migrate at both the individual level (Todaro, 1969; De Jong & Gardner, 1981), and at the household level (Massey & Garcia, 1987; Mincer, 1978; Galarza & Yancari, 2005). However, research on economics and psychology have pointed out that

besides the economic factors, there are achievement motivation and family ties that influence the decision to migrate or to stay (Djaji*ć*, 2008; Mincer, 1978; Tartakovsky & Schwartz, 2001). In this case, a migrant seeks to secure not only his own well-being but also his family members' well-being. Thus, for example, the presence of older parents or children may act as constraints to the potential migrant or migrant household and may change the migration decision.

Other studies explain migration according to an investment approach that suppose a cost-benefit analysis made by the migrant that includes a comparison of different conditions and opportunities at the origin and the destination (Falaris, 1979). The labor migration theory explains migration decisions based on job market characteristics, including wage differentials, unemployment rates, and the growth rate of employment (Harris & Todaro, 1970; Massey, 1990; Muth, 1971; Pessino, 1991). Finally, many researchers have investigated the effects of migration on income and expenditure levels of migrants and their families left behind, including possible impacts on productivity of agricultural activities (Morrison, 1993; Ortega-Sanchez, 2001; Ortega-Sanchez & Findeis, 2001), and the effects on income in the origin community through remittances (Galarza & Yancari, 2005; Taylor, 1999).

Migration theory states that the decision to migrate is based on utility or income maximization; hence, it is expected that the consequences of migration should be positive in the net sum. Generally, economic approaches explain utility levels in terms of wealth status, implying a positive relationship between wealth and happiness or life satisfaction (Graham & Pettinato, 2000). But, life satisfaction involves more than only economic variables such as wealth or income. Life satisfaction also includes multiple aspects of human life, e.g., health status, education, quality of

family life, and job satisfaction (De Jong et al., 2002; Diener, 2000; Findeis et al., 2005; Severin, 2011). Not only having a job but also keeping the family together have been argued as important factors for immigrant parents (Djajić, 2008).

Studies have documented lack of a clear relationship between income and happiness known as the *Easterlin's puzzle – why* a higher income does not imply a higher happiness score (McBride, 2001; Easterlin, 2001). Moreover, researchers have found no relationship between income and happiness when employment and education are included as control variables (Oswald, 1997; Veroff et al.,1981). Similar to *Easterlin's puzzle*, immigrants very often report happiness scores at the destination lower than those reported by the rural population left behind at the origin -- contrary to migration predictions and in spite of having a higher mean income. De Jong et al. (2002) for Thailand and Knight & Gunatilaka (2008) for China found that there exists a negative relationship between migration and well-being. Likewise, Graham & Pettinato (2000) found no relationship between income and happiness among internal migrants in Peru.

Given the above observations about migration and happiness, the question that arises is: if immigrants are not satisfied with their well-being at the destination, why is the migration flow still high[1] and why do immigrants not leave the destination for another subsequent destination elsewhere? Most of Latin American immigrants do not return to their home country (Mayr & Peri, 2008). That is, there is a gap in our knowledge of understanding the relationship between migration and subjective well-being (happiness or life satisfaction). A potentially *key variable* that most applied

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[1] According to the United Nations Population Division, the stock of immigrants in the U.S. grew from 13,991 thousand (6.4% of total population) in 1975 to 42,813 thousand (13.5% of total population) in

studies do not consider in analyses is consideration of the well-being of *"the next generation"*. Based on a homogeneous group, such as immigrant farmworkers, this paper attempts to extend the literature in happiness and migration by incorporating *the next generation* in the equation to explain the *migration puzzle*. This paper attempts to contribute to the understanding of the next step after the initial migration, to understand *why (unhappy) migrants do not leave a place*. The hypothesis proposed is that children's well-being may sway migration decisions in their households.

This study differs from previous ones in several aspects. First, due to the nature of the data used for the empirical estimation, it is possible to compile reported responses of adolescents from immigrant families regarding their overall well-being, education and expectations with respect to migration. Second, it explores a topic hardly studied – i.e., the role of children's well-being in the decision to migrate. However, there are limitations in the approach. The data are cross-sectional, and a cross-sectional analysis does not allow observing the *t+1* moment decision of migrating; instead previous migrations will be used as a proxy to analyze decisions to migrate or to stay, as suggested by Pessino (1991) who employed previous migrations (direction of the last move) to explain sequential migration. The analysis will be complemented by a latent class analysis (LCA) to determine the likelihood of being a migrant or stayer, and by using a latent class regression (LCR) to explore the influence of the next generation in migration decisions. Finally, due to data limitations, it is not possible to control by years since the last migration, but instead the variable 'parent's identity as U.S. citizen' will be included to control for attachment to the new destination and assimilation into the host culture.

The remainder of this paper is divided in four sections, including the model, data, estimation strategy and variable definitions, and research conclusions.

The model

Models of migration decisions at the household level, overlapping generations and sequential migration models are considered as the foundation for this section.

Following overlapping generations model, it is assumed that the entire population is divided in two age groups, youth and old-age or children and parents as it is the case in this article. Let us consider that there are two generations, '*the first generation*' includes international migrants who are the parents, and the second generation is '*the next generation*' who are the children of the first generation. The word "next generation" instead of "second generation" is used because the main interest is the children of migrant families even if those children are migrants themselves. Decisions related to migration are undertaken by the first generation; the first generation will be called *generation t*, and the next generation called *generation t+1*.

According to sequential migration theory, the migrant has three options: (1) to stay, (2) to move back to the origin, and (3) to move out again to another destination, depending on his/her experience in the current location of residence. However, following household decision models, generation t will make a decision taking into account not only his own experience but also generation t+1 experience in the new area. Authors like Nivalainen (2004) and Swain & Garasky (2007) have found that fathers are tied-stayers, i.e., *they maximizes family well-being rather their own well-being*. Parents consider in their decision-making process factors as having the family

united and the future of their children in economic and social facets (Nivalainen, 2004). Hence, it is expected that next-generation well-being will enter as a determinant in the migration decision equation.

Following Pessino (1991) and incorporating some modifications, the model proposed in this research considers two locations, location 1 and location 2. To specify the time frame, assume two periods, in period 1 the family is located at a foreign country knows as "origin", during period 2 the family has moved to Pennsylvania (location 1) known as "destination". In period 2, both generations have experience and know their well-being in location 1, then by the end of period 2 generation t should decide whether or not to stay in the Pennsylvania. However, during period 2, generation t does not know the well-being in location 2 (when location 2 is different from location 1).

Once generation t has migrated to U.S. and moved to Pennsylvania (PA), there are two options, stay in PA or move out to a new destination. PA is the *location 1* selected to live during period 2, by the end of period 2, a new location or *location 2* (PA or other state) will be selected given that PA was previously selected.

Figure 1 – Migration flow
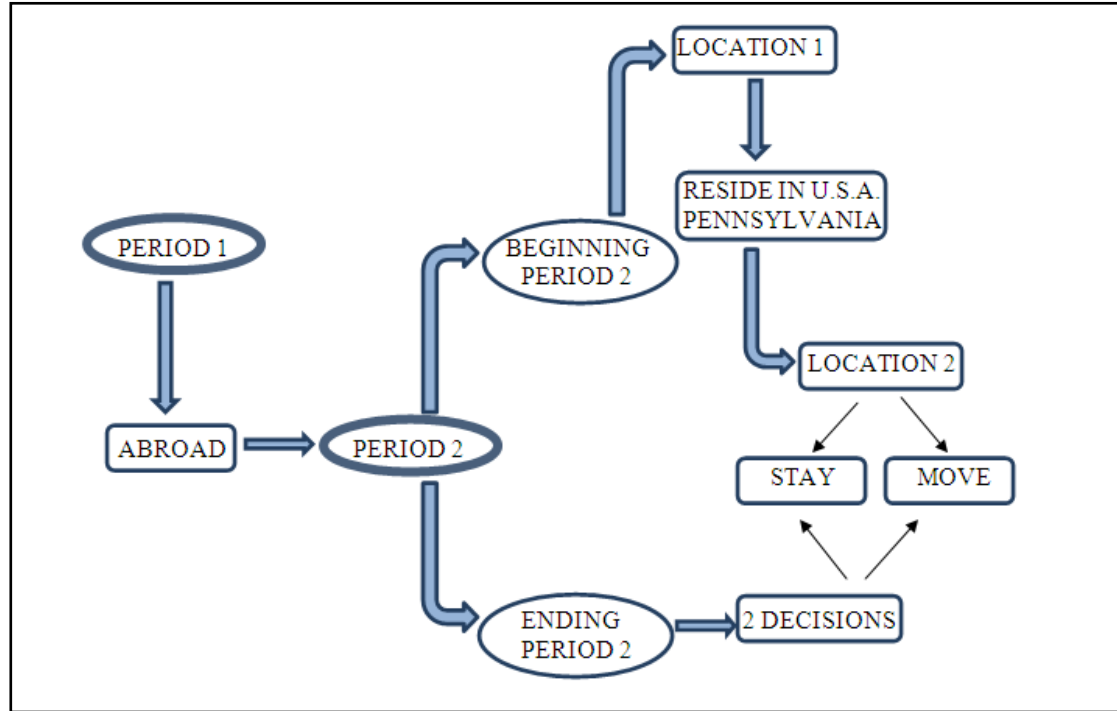
In each location, *generation t* observes two outcomes/rewards, $X_{i,t}$, which represents the reward for generation t, and $X_{i,t+1}$, which represents the reward for generation t+1, with i=1, 2 (location). In this article, the reward is associated to well-being and education[2] for children (generation t+1), and job well-being for parents (generation t).

The values for $X_{i,t}$ and $X_{i,t+1}$ are known when location i is selected, that is, $X_{i,t}$ and $X_{i,t+1}$ are unknown before migration. Following Pessino (1991) and Miller

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[2] As it was stated in the introduction, well-being comprises many dimensions of human life. Education for children is a good indicator of happiness in the long term.

(1984) it is assumed that a priori, $X_{i,\bullet}$ follows a normal distribution, $X_{i,t} \sim N(\theta_i, \sigma_i)$

and $X_{i,t+1} \sim N(\phi_i, \varphi_i)$. Then, the reward for each generation can be expressed as:

$$X_{i,t} = \theta_i + \sigma_i \xi_i \qquad \xi_i \sim N(0,1)$$

$$X_{i,t+1} = \phi_i + \varphi_i \omega_i \qquad \omega_i \sim N(0,1)$$

$\theta_i \neq \phi_i$, because each generation has different beliefs about the reward in any

location previous to migration.

$\sigma_i \neq \varphi_i$ and $\xi_i \neq \omega_i$, the terms $\sigma_i \xi_i$ and $\varphi_i \omega_i$ are the noise of the process

because generation t and generation t+1 cannot match exactly their previous beliefs

with the actual reward.

Assuming no discounting and no moving costs, the overall reward of a

household in each location is given by $Z_i = X_{i,t} + X_{i,t+1}$. Assume that S_i is

experience accumulated in location i:

$$S_1 = X_{\tau(0),t} + X_{\tau(0),t+1}, \qquad \tau(0) = i = \text{initial location.}$$

$$S_2 = X_{\tau(S_1),t} + X_{\tau(S_1),t+1}, \qquad \tau(S_1) = i = \text{location selected after initial location.}$$

S_i collects information about the reward for each generation at every location.

The objective is to select $\tau(0)$ and $\tau(S_1)$ that maximizes V_i, such as:

$$\max_i V_i = E\left[\sum_i S_i\right], \qquad \text{E is the expectation operator.}$$

Thus, *the focus of this research is during period 2 (after experience in*

location 1) when the immigrant decides to move again or to stay. Additional controls

for the next generation and parents include: age, educational attainment, and family

structure.

Data

The data employed for this research paper is based on the "Survey of Migrant and Seasonal Farm Worker Youth – A Study Conducted by The Pennsylvania State University, 2006" in collaboration with the Lincoln Intermediate Unit of the Pennsylvania Migrant Education Program (MEP) and Rural Opportunities, Inc. headquartered in Rochester NY (ROI, now Pathways).

The survey was conducted only in the southeastern Pennsylvania; it was a one-time survey among adolescents in migrant and seasonal farmworker families; survey participants began to be enrolled in late 2006 and incorporated new participants until early 2008. The Pennsylvania counties considered in the survey were Lebanon, Adams, York, Lancaster, Delaware, and Chester. The target population was international immigrants working in farm activities, agricultural jobs in specific. The studied population was comprised largely of Latin American immigrants: 74.6% of youth respondents were from Mexico (or of Mexican heritage), 17.1% from other Latin American countries[3], 3.9% were born in the U.S. and 4.4% were from Cambodia.

For this research, the focus is only on the youth population from migrant and seasonal farm worker families. Thus, the data contain information about family migration history of all families with children. The sample for the youth population contains 307 observations, including adolescents and a small set of young adults; however, for some observations there is not 100% complete response for each

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[3] Other Latin American countries include Colombia, Cuba, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Peru, and Puerto Rico.

question. The age range is 12 to 25 years old, and the average age is 15.9 years. The survey collects information from three groups: younger high school students (grades 8 through 10), older high school students (grades 11 and 12), and secondary school drop-outs, in order to avoid a problem of sample selectivity due to attrition from (dropping out of) school.

The survey focused on life experience, aspirations, and expectations of the youth population. The survey asked about educational attainment, family structure, parents' characteristics, and migration history. Other questions were related to work history, health, ethnic background, community ties, and language barriers.

Estimation Strategy and Variable Definitions

First, it is necessary to clarify that the data only consider international immigrants; that is, the analysis is based on the post-migration movements once the immigrant has entered the U.S., then moving costs within the U.S. are negligible.

One of the main problems in migration studies is "selectivity bias" in the data -- i.e., people who decided to migrate are not randomly distributed. However, one advantage of this study is that the survey gathers information from people who have already experienced international migration, that is, they share similar characteristics and personal attributes that make them more likely to opt for migration. Likewise, the data comprise a homogenous group of immigrants from Latin American[4] (mostly from Mexico) with similar skills as farmworkers.

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[4] Mayr & Peri (2008) based on U.S. data showed that Latin Americans have a different return migration pattern in comparison to migrants from Eastern Europe and Asia. There is almost no return migration among Latin Americans immigrants.

This case is a good example to analyze only next generation effect on parents' decision. Parents are a homogenous group working as farmers in PA who face a similar wage in PA and nearby state comprises in the Northeast Region II. Thus, wage is not a factor to determine migration's decision because the other potential locations are not offering a wage differential.

There are two approaches in the estimation strategy proposed. The first approach uses a logit analysis using the statistical package STATA 9. The second approach is based on a latent analysis regression (including latent analysis classes) using the statistical package R 2.13.0.

In the first approach, the immigrant in location 1 (PA) will decide whether to migrate or to stay according to:

$$DecMig = \alpha_0 + \alpha_1 X_{it} + \alpha_2 X_{it+1} + \alpha_3 Z + \varepsilon$$

Z includes control variables such as parents' educational attainment, family structure which includes civil status of parents and if the child lives in a nuclear family or extended family (with aunts and uncles). For this model, information about previous migration toward Pennsylvania is used as a proxy for likelihood of migration. The data collected show that 29.7% has stayed in PA., 16.6% migrated from a different town but within PA., 11.6% migrated from a different county but within PA., 16.1% migrated from different state, and 26.1% migrated from foreign origins. The responses are divided into two groups, (1) those who stayed in PA (town and county) – who are more likely to be stayers in the future -- and (2) those who migrated from other states.

To control by next generation, two variables are considered: well-being and education. The survey asked to children (next generation) if they are satisfied with

the overall well-being of their family. Survey responses show that 18.4% are very

satisfied, 49.3% are satisfied, 24.8% are neutral (neither satisfied nor unsatisfied), 6.0%

are unsatisfied, and 1.5% are very unsatisfied. Next generation well-being is grouped

into three categorical responses: satisfied, neutral, and unsatisfied.

In the case of education, school levels are included to measure educational

attainment of the next generation[5]. The survey considers not only children in high

school but also children who dropped-out school and already graduated. The survey's

question is: "what grade are you in now or if it is now summer, what grade will you

be in this coming fall?" There are 13.1% respondents in 8th grade, 19.8% in 9th grade,

21.5% in 10th grade, 14.8% in 11th grade, 11.4% in 12th grade, 6.0% has dropped-out

the school, and 13.4% has already graduated or have a GED. This variable is grouped

into four categories, drop-out, middle school (8th grade), high school (9th grade

through 12th grade), and already graduated or with a GED.

To control for parents' well-being, the variable job well-being is used, with the

response from child's point of view. The survey includes a question about the mother

and father -- if they like their jobs. In the case of fathers, the responses show that 11.8%

believe that their fathers strongly like their jobs, 37.1% only like their jobs, 15.2%

neither like nor dislike, 8.9% dislike their job, 2.1% strongly dislike their employment,

and 24.9% does not know. In the case of the mother's job, responses show that 9.7%

believe that their mothers strongly like their jobs, 35.5% only like their employment,

18.9% neither like nor dislike, 8.8% dislike their job, 0.4% strongly dislike their job,

and 26.8% does not know. These two variables are grouped into: 1) like job (includes

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[5] As pointed out in the introduction, education is an important aspect of life satisfaction.

strongly like and like), 2) neutral (neither like nor dislike), and 3) dislike job (includes

strongly dislike and dislike).

The dependent variable, migration, is a dichotomous variable and the best

strategy of estimation is to use a logit model. Logit models are estimated to analyze

the likelihood of migrating, with (Y = 0) for moving and (Y = 1) representing staying.

The likelihood function to be estimated is: $L = \prod_{Y_i=1}\left[1 - F(-\beta'X_i)\right] \bullet \prod_{Y_i=0} F(-\beta'X_i)$ with

$F(-\beta'X_i) = 1/\left[1 + \exp(\beta'X_i)\right]$ (Maddala, 1991). There are two models to estimate, one

model includes next generation well-being as the main independent variable, and the

second model includes education level of the next generation. Descriptive statistics of

the variables employed in the logit estimations are presented in Table 1.

Table 1 – Descriptive statistics

Variables	Obs	Mean	Std. Dev
Migration decision (1=stay in PA)	147	0.7823	0.4141
Next Generation			
Well-being			
Unsatisfied	266	0.0752	0.2642
Neutral	266	0.2481	0.4327
Satisfied	266	0.6767	0.4686
Education			
Drop-out	298	0.0604	0.2386
Middle school	298	0.1309	0.3378
High school	298	0.6745	0.4694
Already graduate or GED	298	0.1342	0.3415
Father			
Unsatisfied	178	0.1461	0.3542
Neutral	178	0.2022	0.4028
Satisfied	178	0.6517	0.4778
Years of education	136	7.0147	3.5963
Mother			
Unsatisfied	167	0.1257	0.3326
Neutral	167	0.2575	0.4386
Satisfied	167	0.1257	0.3326
Years of education	151	8.0199	4.4862
Familiy structure			
Parents live together	235	0.7319	0.4439
Live with extended family	241	0.3444	0.4762

In the second approach, LCA and LCR are employed. LCA is a statistical technique which allows dividing a population into exclusive classes by comparing different models. These models assign the population to latent classes such as two classes or three classes to determine the best model by comparing their statistics.

LCA is similar to a factor analysis but it is a better instrument for categorical latent variables. Besides, LCA is preferred over a cluster analysis because LCA does provide the probability of being classified within a category meanwhile a cluster analysis only put population into groups. A main assumption in LCA is local independence; observed variables (Y_i) are independent within latent classes (X_j), if an individual belongs to latent class X_1 then it is only reported one outcome of Y,

$$P(Y = y \mid X = x) = \prod_{i=1}^{I} P(Y_i = y_i \mid X = x).$$ Then the probability of obtaining a pattern

of outcomes by using the observed variables is the weighted sum of $P(Y = y \mid X = x)$,

$$P(Y = y) = \sum_{j=1}^{J} P(X = x) \prod_{i=1}^{I} P(Y_i = y_i \mid X = x).$$ Using Bayes' formula, the probability

of belonging to each latent class is calculated,

$$P(X = x \mid Y = y) = \frac{P(X = x) P(Y = y \mid X = x)}{P(Y = y)}.$$ The parameters of LCA are estimated

by a maximum likelihood procedure (Linzer & Lewis, 2011; Vermunt & Magidson, 2004). According to the model proposed, migration decisions are divided into stayers and movers (migrants); this classification is confirmed by the LCA. The findings indicate that the two-class model is more appropriate considering Bayesian information criterion (BIC) and Akaike's information criterion (AIC)[6] with lower values for BIC and AIC being preferred. LCA confirms that taking into account variables such as previous migration, remittances, parent's identity, and family structure, the data can be divided in two categories, (1) those with more probability to

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[6] The two-class model reports BIC equals to 959.1893 and AIC equals to 898.7183 meanwhile the three-class model reports BIC equals to 965.1129 and AIC equals to 873.197.

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be a stayer (family), and (2) those with more probability to be a migrant (family). In line with previous literature (Nivalainen, 2004; Osili, 2007; Swain & Garasky, 2006) indicators of being a stayer are: living in a family that not often or never send remittances, living with parents who are not married, and living with extended family (aunts, uncles, and other relatives).

The second step in this approach is to use LCR or '*latent class models with covariates*' to estimate a regression model when the dependent variable was classified into latent classes. In this article, there are two regression models, both models have the latent variable migration (classified into stayer or mover) as dependent variable, and in one model next-generation well-being as a covariate variable, and next-generation education as a covariate in the other model. Using the program **polCA** in R (Linzer & Lewis, 2011), the latent class regression is estimated by the "one-step" technique to avoid generating biased coefficients. One main assumption of LCR is that the prior probability of belonging to a latent class varies depending upon the observed covariates by individual (p_{jn}) with $\sum_{j=1}^{J} p_{jn} = 1$ for each individual. Let assume Z_n covariates for each individual (n), then poLCA will calculate the log-odds of the latent class with respect to the reference class which is arbitrarily selected (class=1), such as, $\ln\left(p_{2n} \middle/ p_{1n} \right) = Z_n \beta_2$. In the next step, poLCA uses a modified expectation-maximization algorithm to calculate $\hat{\beta}_j$ and $\hat{P}(Y = y \mid X = x)$ to calculate the posterior probabilities of belonging to a latent class and to updated the coefficients of the covariates (Linzer & Lewis, 2011).

Results

For the first approach, marginal effects of the logit models are presented in Tables 2 and 3. Table 2 summarizes the results of the logit model including well-being for the next generation as the main independent variable. Table 3 then shows the results of the logit model with education variables as the main indicator to explain migration decisions. The variables included are added to the estimation as blocks, that is, the independent variables are divided into groups for the next generation, father, mother, and family structure.

Table 2 presents four models. Model 1 includes only next-generation well-being and father job satisfaction, model 2 adds mother job satisfaction, model 3 includes years of education of parents, and model 4 is the full model with next-generation, parents, and family structure variables. Results indicate that families with children reporting a 'satisfied' level of well-being are more likely to stay in PA even when controlling by parents' job satisfaction (model 1 and model 2) and by parents' years of education (model 3). These results validate the hypothesis that parents' migration decisions take into account the child's well-being, consistent with the results found by Nivalainen (2004) and Swain & Garasky (2007) that fathers are tied-stayers. However, once the model is controlled by family structure variables, the next-generation well-being variable loses statistical significance; hence, it seems family structure variables and next-generation variables have similar effects on migration decisions.

Table 3, similar to Table 2, shows four models: model 1 includes only next-generation education level and father job satisfaction, model 2 adds mother job satisfaction, model 3 incorporate years of education of parents, and model 4 is the full

model. Controlling by parent's job satisfaction, the results show that families with children doing well in the school who did not drop-out and are still attending school, are more likely to stay in PA. That is, it is important for parents that their children are doing well in school, even controlling by their own job satisfaction. However, similar to the results in Table 2, the full model (model 4) indicates that next-generation are not significant when family structure variables are included in the analysis, suggesting that both groups of variables pick up the same effect.

Table 2 – Well-being as main indicator

Stayer (=1), Mover (=0)	Model 1	Model 2	Model 3	Model 4
Next Generation				
Unsatisfied (1=yes)	0.142	0.132		-0.143
	1.39	0.93		-0.42
Satisfied (1=yes)	0.244**	0.304**	0.390**	0.037
	2.23	1.96	1.67	0.24
Reference category: neutral				
Father				
Unsatisfied (1=yes)	0.179			
	1.87			
Satisfied (1=yes)	-0.079	-0.054	-0.004	-0.019
	-0.79	-0.41	-0.03	-0.14
Reference category: neutral				
Years of education			-0.025	
			-1.41	
Mother				
Unsatisfied (1=yes)		0.100	-0.059	0.091
		0.61	-0.27	0.61
Satisfied (1=yes)		0.184	0.055	0.243*
		1.28	0.45	1.65
Reference category: neutral				
Years of education			0.004	
			0.28	
Familiy structure				
Parents live together (1=yes)				-0.031
				-0.18
Live with extended family (1=yes)				-0.245
				-1.1
Log-likelihood function	-50.8451	-37.1908	-14.3827	-32.0280
Number of observations	100	71	42	64

* $p<.1$; ** $p<.05$; *** $p<.01$

Table 3 – Education as main indicator

Stayer (=1), Mover (=0)	Model 1	Model 2	Model 3	Model 4
Next Generation				
Middle school	0.213*	0.237		0.040
	2.82	2.20		0.15
High school	0.363**	0.491**		0.143
	1.92	2.09		0.48
Already graduate or GED	0.188	0.282	-0.033	0.148
	2.02	2.26	-0.25	0.80
Reference category: drop-out				
Father				
Unsatisfied (1=yes)	0.131			
	1.07			
Satisfied (1=yes)	-0.061	-0.030	-0.028	-0.017
	-0.58	-0.22	-0.17	-0.13
Reference category: neutral				
Years of education			-0.033	
			-1.33	
Mother				
Unsatisfied (1=yes)		0.112	0.017	0.089
		0.70	0.09	0.58
Satisfied (1=yes)		0.171	0.059	0.245
		1.13	0.39	1.54
Reference category: neutral				
Years of education			0.007	
			0.39	
Familiy structure				
Parents live together (1=yes)				0.044
				0.20
Live with extended family (1=yes)				-0.217
				-0.95
Log-likelihood function	-50.0205	-36.7028	-15.9486	-31.4917
Number of observations	101	70	38	63

* p<.1; ** p<.05; *** p<.01

For the second approach, the latent class regression results are presented in Table 4, with graphics included for a better understanding of the results. A two-class model was run considering next-generation and father variables as covariates. Table 4 shows the coefficients estimated, model 1 and model 2 consider next-generation well-being[7] as the main indicator, whereas model 3 and model 4 consider next-generation education[8] as the main indicator. The program poLCA arbitrarily selects the reference class (Linzer & Lewis, 2011), in the four models presented, "be a stayer" is selected as the reference class.

Table 4 – Latent Class Regression

|	Model 1	Model 2	Model 3	Model 4
Next Generation Well-being	0.617* 1.72	-1.274 -1.27		
Education			-0.195 -0.54	-1.610 -1.72
Father				
Satisfaction with his job		-1.137 -1.16		-1.153 -1.18
Intercept	-1.953 -2.17	5.454 1.71	-0.120 -0.11	3.068 1.10
Maximum log-likelihood	-419.6450	-395.4857	-415.4979	-395.1109
Number of observations	82	79	82	79

* p<.1; ** p<.05; *** p<.01

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[7] The next-generation well-being is categorized from 1 (very satisfied) to 5 (very unsatisfied).

[8] The next-generation education is categorized from 1 (dropped out of school) to 4 (already graduated/GED).

The results in Table 4 for model 1 and model 2 show that next-generation well-being has a significant effect on the likelihood, that is, if children report a lower satisfaction then they are more likely to pertain a mover family. As it is showed in Figure 1, if next-generation reports being very satisfied the probability of being a stayer is higher than the probability of being a migrant (mover), meanwhile if the children report being very unsatisfied then the probability of being a migrant is higher than the probability of being a stayer. However, well-being of children is not significant when the model is controlled by father's job satisfaction.

Figure 1 – Next-generation well-being as covariate
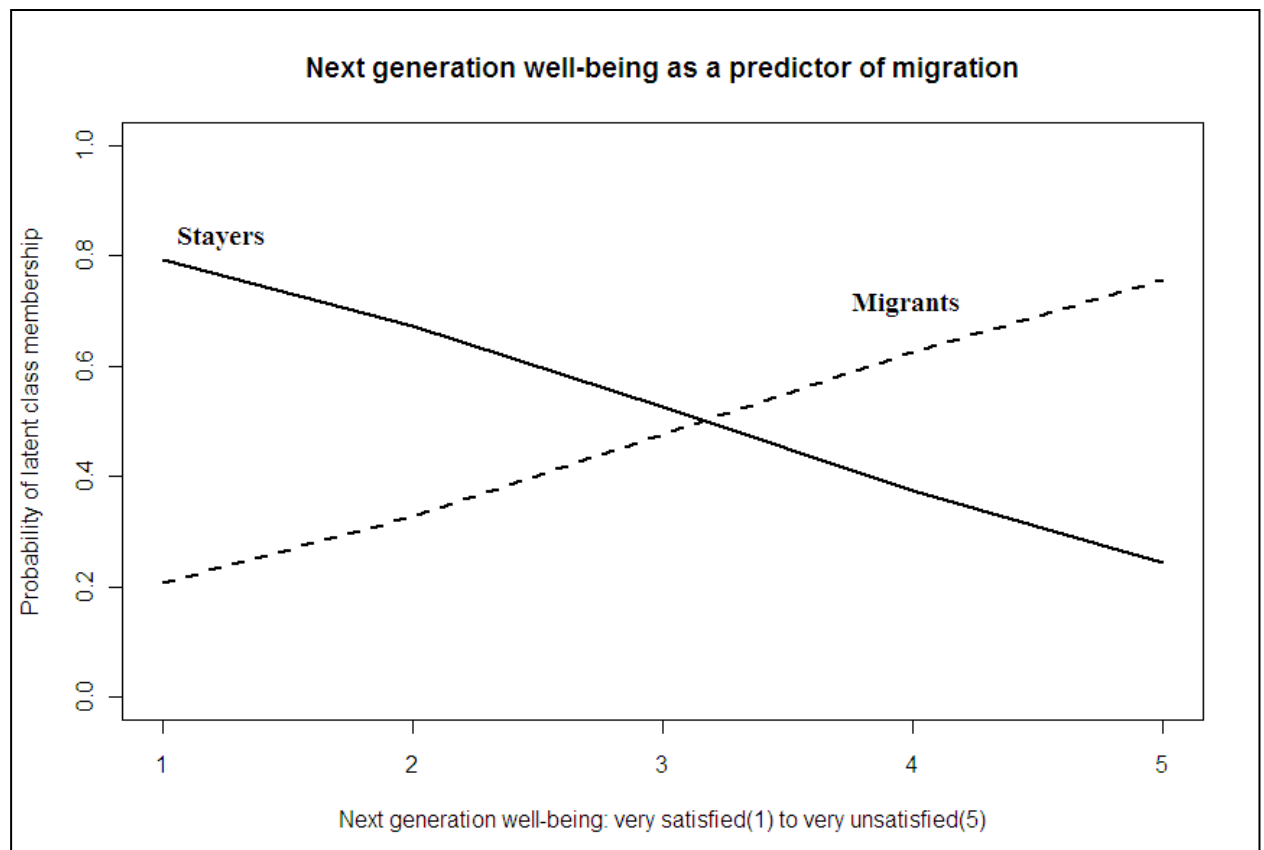
Results in model 4 show that when controlling by father's job satisfaction, the education of the next-generation has a significant effect on migration decisions. Thus, it is more likely to be a stayer family if the child is still in the school. Figure 2 shows that if the child drops out the school then there is a lower probability that the family stays.

Figure 2 – Next-generation education as covariate
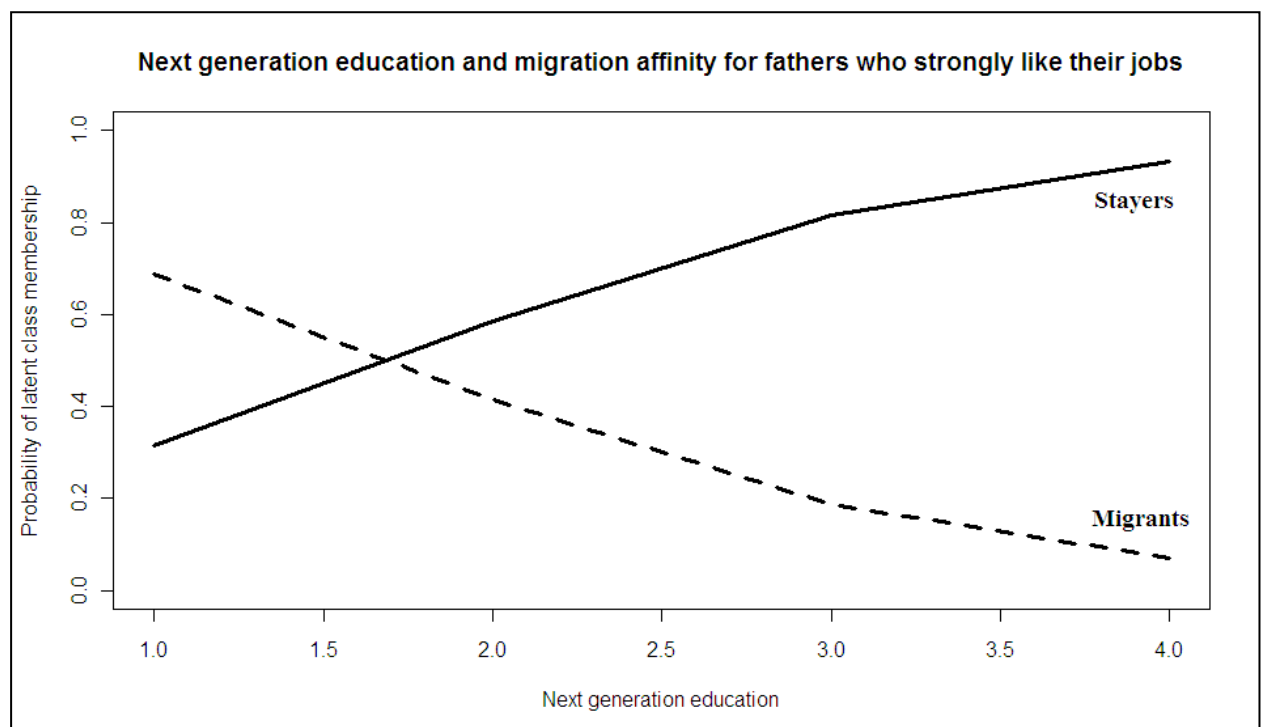
Conclusions

This article intends to contribute in the understanding of migration decisions by including next-generation in the equation. In spite of the small number of observations, the results using two different methods, a logit estimation and a latent class regression, show that parents' decision-making about migration takes into consideration their children well-being and educational achievement. Thus, if

children report being satisfied with their well-being, it is more likely that parents decide to be stayers. Similar, if children are doing well in school by continuing with their studies, it is more likely that parents decide to be stayers, as well. Additionally, it is important to highlight the importance of family structure variables, such as living with an extended family, in the migration decision. The main contribution of this paper, it is to show that there are other factors, besides job, such as next-generation to understand migration decisions of immigrant parents.

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