ABSTRACT

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Migration is often thought of as a risky endeavor in which a migrant trades a known low return for an unknown but potentially higher return. However, migration has been empirically linked to insurance mechanisms through remittances. Chapter 1 unifies the risk-taking and insurance-seeking behaviors of migration into a single framework by framing the migration decision as one of income diversification in which multiple agents within a household to decide whether or not to migrate. Each migration strategy (no migration, partial migration, and full household migration) has its associated risks which are weighed against the returns the household could gain through choice of that particular migration strategy. I test the framework by estimating the probability of each migration strategy for Indonesian households during the period 1993-1998. The framework performs reasonably well in the case of urban households. However, the framework's predictions do not hold as well for rural households, which may be linked to the fact that they function within a larger insurance network than the nuclear family.

In Chapter 2, I find that the response of return migration to GDP per capita can differentiate migrants who are seeking increased consumption for their household (i.e., consumption-oriented migrants) from migrants with intentions to invest at origin (i.e., investment-oriented migrants). Each type of migrant should have differential responses to GDP per capita at destination and may have differential responses to GDP per capita at origin. Using data on Mexican households between 1992-2002, I show that migrants returning from the USA exhibit characteristics of consumption-oriented migrants and migrants returning from internal locations exhibit characteristics of investment-oriented migrants.

Chapter 3 is a published work in collaboration with Sandra Decker, Jalpa Doshi, and Daniel Polsky which uses Medicare claims data linked to two different surveys—the National Health Interview Survey and the Health and Retirement Study—to describe the relationship between insurance status before age 65 years and the use of Medicare-covered services beginning at age 65 years. Although we do not find statistically significant differences in Medicare expenditures or in the number of hospitalizations by previous insurance status, we do find that individuals who were uninsured before age 65 years continue to use the healthcare system differently from those who were privately insured.

ESSAYS ON MIGRATION AND HEALTH INSURANCE

By

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Dedication

To the people of Aguerda for showing me a whole new way to live

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Introduction

This dissertation contains three essays about rethinking why simple anticipated relationships are overlooking deeper effects. In the first chapter, I reconcile the risk-taking and risk-insuring behavior of migrants which have previously been studied only in isolation from one another. In the second chapter, I show that discussions on harnessing remittances and return migration are overlooking a potentially valuable source of development: internal migration. In the third chapter, a published work in collaboration with Sandra Decker, Jalpa Doshi, and Daniel Polsky, we show that justifying the expansion of health insurance coverage with potential Medicare savings overlooks the continued differences in post-Medicare health services usage by pre-Medicare insurance status.

All three essays use observable correlations to try to draw deeper conclusions by excluding alternatives. Each chapter takes an observed correlation and postulates how this correlation may have been generated. This hypothesis is then tested with the available data. Each of the essays, in turn, demonstrates how a simple explanation of the phenomenon at hand causes one to draw policy conclusions that are different from those that would be drawn from the analysis performed here.

First, if we consider all migrants to be risk-takers going after higher wages, we might want to implement a policy of subsidized wages in the origin communities in order to reduce population pressures from rural-urban migration. This simple wage-seeking relationship overlooks the effect of differing levels of risk aversion on migration behavior that lead some migrants to engage in risk-insuring migration. Those migrants who are risk-insurers will be less likely to change their migration behavior in response to a subsidized wage since they are looking for ways to smooth their consumption. Thus, a policy providing better access to insurance might have better results.

Chapter one explores this correlation in more detail. Specifically, it uses correlation in incomes across locations to explain both risk-taking and risk-insuring migration. I postulate that migration behavior can be characterized as an income diversification problem in which a household decides where to locate each of its members. In this framework, the observed correlation between the number of migrants in a household and the correlation in incomes between home and away locations helps account for both of these types of behavior. I test the framework using data on Indonesian households.

Second, a belief that it is the lack of funds in origin communities that stifles development will lead us to consider how to facilitate the transfer of international remittances to origin communities. In doing so, we overlook the motivation behind sending the remittances. If the motivation is to increase consumption in the receiving household, then our policy is unlikely to have strong influences on development activities in the origin communities. If, however, the motivation is to increase capital for investment, then our policy is likely to have the intended effect.

Along a similar vein, if we focus on the relationship between high skill international return migration and development in the origin community, we may want to implement a policy to encourage the return of international migrants. In doing so, we overlook a large portion of the migrant population of countries such as Mexico who may already be focused on investing in their origin community and may benefit from policies which facilitate the formation of investment capital, be it financial, human, or social capital that is needed.

Chapter two explores the correlation between return migration and the motivation to invest in the home community. Specifically, it uses the timing of return during the business cycle to distinguish between migrants who are mainly focused on increasing consumption and migrants who are mainly focused on obtaining capital for investment. I claim that the motivations behind seeking consumption versus investment capital is likely to lead to different choices about when to engage in return migration. I use the observed correlation between the business cycle and a migrant's return to distinguish between these types of migrants. I test this relationship using international and internal migrants from Mexico.

And third, if we only look at expenditures of Medicare recipients, we may believe that expanding health insurance coverage will bring about changes in health service usage that will lower costs. However, doing so would overlook the way in which those individuals without insurance pre-Medicare continue to use Medicare services differently from those who had insurance prior to becoming eligible for Medicare. It is, therefore, possible that expanding health insurance coverage may not have the intended results.

Chapter three is a joint work with Sandra Decker, Jalpa Doshi, and Daniel Polsky that was published in *Health Economics* (2012) that explores the correlation between pre-Medicare insurance status and post-Medicare expenditures from a new angle. In this chapter, we use post-Medicare health service usage to show that expanding health insurance coverage may not have the intended effect of reducing Medicare expenditures. We postulate that differences in the usage of health services upon Medicare eligibility may be due to pre-Medicare insurance status. These differences may then lead to no reduction in Medicare expenditures. In addition, we show that methodology matters when one is using the observed correlation between health service usage/Medicare expenditures and pre-Medicare insurance status.

Chapter 1: Risk, Consumption Insurance, and Migration

1 Introduction

Immigration often involves trading a safer outcome in one's home for a higher, but riskier return in one's destination, thus implying that migration is a risk-taking behavior. On the other hand, migration has been empirically linked through remittances to insurance mechanisms (Rosenzweig and Stark, 1989; Paulson, 2000; Yang and Choi, 2007). This paper aims to unify these two motives in a single testable framework and explore its consequences empirically. These two contradicting motives can be reconciled by recognizing that migration does not always involve the departure of the full households, but very often of only a few of its members. Thus, while each individual's migration involves taking risks, it can also provide risk diversification if only some household members migrate and elect a location where the covariance with returns at home are negative (Chen, Chiang, and Leung, 2003).

The next section sets out the framework used to estimate the relationship between the "risk factors" and the decision on the number of migrants. To unify both the risk-taking and the insurance seeking behaviors of migration, I model this decision as an income diversification problem in which a risk-averse household decides where to locate each of its two members. The household can decide to diversify its income across locations or to locate both members in just one of the locations. The expected utility derived from each option is based on both the wages gained and the risks involved in taking that decision.

Not migrating may appear as a safe option since the variance in the home earnings is potentially more known to the household. But it involves some higher exposure to risk since one does not exploit the potential for risk diversification involved in migration. Households can mitigate the risk they face by diversifying across locations under the right circumstances. The key piece included in the model is the correlation in incomes across locations (Chen, Chiang, and Leung, 2003). When this correlation is sufficiently low or negative, a household can decrease their risk by locating one member in the home location and one member in the away location, even when the variance of income in the away location is higher than that of the variance of income in the home location. Finally, households that are the least risk averse may elect to take the riskiest option of all, moving the entire household in the hopes of higher returns.

In subsequent sections, I estimate the probability of each migration strategy (no migration, partial migration, and full household migration) in the context of Indonesia. I use individual and household data from 1993 to 1998 collected in the Indonesian Family Life Survey (Strauss, Beegle, Sikoki, Dwiyanto, Herawati and Witoelar, 2004; Frankenberg and Thomas, 2000) to test the framework. The IFLS is particularly useful in this context because it collects detailed migration data. These data provide not only information on whether someone moved, but when the move occurred, where the household member moved to, and whether anyone else in the household accompanied them. Since most of the sample does not move, I constructed a counterfactual migration destination for nonmigrant households using moves recorded prior to the sample period. I assigned to nonmigrant households the "best option" available to the household. The best option was determined by finding the most common destination for both partial and full migrant households, calculating the utility a nonmigrant household would have derived from exercising each option, and then assigning the household the destination associated with the option with the highest utility. I combined this data with district level GDP per capita, district enrollment rates, and the risk factors calculated from a proxy for income in order to estimate the probabilities of the different migration choices.

Income presents a problem when moving to the estimation of this relationship. Income is likely correlated with characteristics of the household not captured in the model leading to omitted variable bias. In addition, income levels and associated fluctuations will be the result of the migration decision. To avoid both the omitted variable bias and reverse causality, I use rainfall to capture the exogenous variation in income. It is perhaps most obvious that incomes will be correlated with rainfall in agricultural areas. But it is also likely that rainfall will be correlated with incomes of those working in tourism, construction, and the manufacturing of foodstuffs and other agricultural related items. Together these categories account for 77% of the jobs held by men who reported an industry code, and 84% of the jobs held by women who reported an industry code. While approximately 50% of all migrants in the dataset go to major cities, these migrants still report working in agriculture (19%) and the manufacturing of foodstuffs (29%) and thus will be impacted by variations in rainfall. In addition to showing which industries migrants report working in, regressing the variance of GDP on the variance of rainfall shows that it is a good predictor of variance in GDP. Thus, it remains likely that incomes in urban areas still depend on rainfall for a majority of migrants. This proxy will be a problem if it captures relationships between locations other than the ones related to risk. Since geographically close sites would have high correlation, distance and distance squared were added to the regression.

The model predicts that home variance, destination variance, and covariance between locations will play a part in the decision to be a partial migrant household, but that only home variance and destination variance should play a part in full migration. The estimation results indicate that households favor safer locations and avoid risky ones. The base estimation which does not control for household type (urban/rural, rich/poor, etc.) performs well for partial migrant households. All of the risk factors are significant and high home variance spurs partial migration while high destination variance and high covariance deter partial migration, just as the model predicts. However, the model performs less well for full migrant households. Home and destination variance are significant for full migrant households, but covariance is still marginally significant (p=0.057) although much less so than for partial migration.

Once I allow the role of the risk factors to differentially impact rural and urban households, I find the model describes more closely the behavior of urban households. The significance of the covariance in full migration disappears for urban households and home variance and destination variance remain significant for full migrant urban households. Destination variance and covariance between locations are significant for partial migrant urban households, showing that they use migration as a risk diversification strategy. However, for rural households the covariance remains significant (p=0.005) for full migration, suggesting that rural households who fully migrate may still diversify their risk by remaining in contact with their location of origin, which is consistent with them being part of a larger insurance network (Geertz, 1962; Geertz, 2006; Ravallion and Dearden, 1988). Home and destination variances have the predicted signs and are all highly significant for rural households.

An alternative explanation for the result that a high covariance inhibits migration is that migrants simply leave in response to a negative shock and go to places experiencing a positive shock. If this explanation holds true, then all households should end up in the same types of locations based on the risk profile. Despite being an anomalous result for my framework, the finding that urban and rural households choose different locations for partial and full migration, both between and among themselves, does not support this explanation. In addition, Tse (2011) shows that migration is actually suppressed in response to several types of natural disasters in Indonesia. While these do not cover all of the negative shocks that could occur for a household, it supports my findings that households are differentiating their locations based upon risk, albeit not always as predicted by the framework.

The model also predicts that more risk averse households should respond more strongly to the risk factors. I explore several proxies for risk aversion that can be derived from the data including wealth, education levels, household size, and landholdings. Given their relationship to risk aversion, we expect poorer households, households with less land, less educated households, and larger households to engage in insurance more often than their less risk averse counterparts, but this is largely not the case in the estimation results. The addition of the wealth index and education level proxies are significant additions to the base equation, but the addition of the landholding and household size proxies are not, as indicated by the likelihood ratio statistics. This makes sense if we consider the ambiguous nature of the effects of landholdings and household size on risk aversion. Greater landholdings will better enable a household to finance a move, but will also create greater ties to the home location. On the other hand, larger households are more constrained in their finances, but are also more likely to have adults other than the household head and spouse who can migrate. Only educational levels differentiate households along insurance lines, with less educated households engaging in partial migration less often in response to a high covariance between locations. Less educated and poorer households engage in partial migration more often in response to a high variance at home, in accordance with the models predictions. The wealth index proxy does not differentiate households along insurance use.

Recent work on the relationship between risk and migration provides possible explanations for my findings. Morten (2012) shows that risk-sharing networks are decreasing with outmigration. Households are becoming more self-reliant and will look to ways to self-insure in a high migration climate. Thus, households in high migration communities should seek more insurance through migration since they do not have the networks to spread their risks over a larger group. While Morten's results support the framework I use, they also provide another explanation as to why the insurance effects may be masked: I am not able to confirm the same in my data since I can measure networks only at the community level and the risk factors that I use cannot be insured at this level. Thus, insurance effects in my results may be muted since I cannot measure larger risk-sharing networks.

Bryan, Chowdhury, and Mobarak (2011) show that the uncertainty of employment inhibits migration in poor households where a negative result of migration is unaffordable. Thus, as in my framework, risk is more important to households at the low end of the wealth scale. In their experiment, migration increased in response to a monetary incentive which did not have to be repaid if there was a negative result of migration. Assuming that some of these households would use migration as insurance, the effect of insurance on location choice would be larger if all households could afford to migrate.

This study supports the insurance motivations of migration and contributes to the wider literature connecting risk to migration in a distinct way from its predecessors. First, previous empirical studies of migration as insurance (Rosenzweig and Stark, 1989; Paulson, 2000; Yang and Choi, 2007)) have focused on behavior which takes place after migration has occurred. In many cases, this is due to lack of data either connecting members of households or connecting migrants to a specific location. As a result, these studies have focused on whether consumption is more likely to be smoothed if a household has a migrant (Rosenzweig and Stark, 1989) or whether remittances are negatively correlated with income movements at the home location (Paulson, 2000; Yang and Choi, 2007). At best, these studies can show that remittance and consumption behavior are "as if" insurance was the motive for migration. This study focuses on the number of migrants in a household, a choice that must be made prior to migrating. In doing so, I am able to show that households are avoiding risky locations and that some households are using migration as insurance.

Secondly, to my knowledge this is the first study to directly estimate the number of migrants in a household. A recent study of cross border migration between the US and Mexico (Lessem, 2011) indirectly estimates the number of migrants in a household. Lessem separately estimates the probability that spouses will migrate. A result of her methods is that one could count the number of migrants at the household level, rather than just looking at how the probability of migration changes for individuals. However, she focuses on how individuals are affected by changes in wages and border enforcement rather than on insurance as is the case with this paper.

The rest of the paper is organized as follows. Section 2 develops the framework. Section 3 discusses the empirical strategy and data. Sections 4 and 5 presents the results of the estimation and robustness tests. Section 6 concludes.

2 Framework

I first develop a framework to establish the incentives households have to migrate. Stark and Levhari (1982) provide an early discussion in the literature of risk as a cause of rural-urban migration. They assume a zero correlation between the urban and rural sectors to motivate their risk diversifying farmer to send a member of the household to work in the city. Chen, Chiang, and Leung (2003) develop a more general model of migration which takes into account the risks involved in migration and allows for correlation in incomes across locations. Their model is similar to the framework laid out below, but is more extensive, taking into account risks which are not directly associated with income earning and allowing for all values of both the returns and risk factors. The framework used here is a simplification of this theoretical framework, focusing on a scenario in which both returns and risks are higher at the destination than at home and looking only at income risks. Anam and Chiang (2007) use a similarly simplified model of risk diversification both across location (rural and urban) and across sectors (formal and informal) in the urban location to explain the persistence of the urban informal sector.

In this setting, households are composed of two risk averse agents. Income is normally distributed with mean μ and variance σ^2. Mean and variance are determined by the location in which income is earned. $\mu_i(x_i, l_i)$ is the expected wage that household member i can earn in his/her chosen location given that household member's characteristics, x_i, and the characteristics of the location in which that member is working, l_i. I assume that the household knows the expected earnings of each member and the variance of earnings in all relevant locations.

There is a set of variances and correlations $[\sigma_i^2, \sigma_j^2, \sigma_n^2, \rho_{ii}, \rho_{ij}, \rho_{ik}, ..., \rho_{nn}]$ over which a household could make their location choice. σ_i^2 is the variance of income in location i. ρ_{ij} is the correlation between the income of location i and the income of location j. I make several simplifying assumptions to contract the space over which I conduct the following analysis. First, I assume that the correlation between earnings within a location ρ_{ii} is one and that the household knows the correlation of earnings between different locations, ρ_{ij}, for all locations $i \neq j$. Second, I assume there are just two locations where the household will consider locating. I call these locations *home* and *away* designated by subscripts h and a, respectively. More generally, one could allow different locations to maximize the household's utility for partial migration and the household's utility for full migration. Doing so does not change the conclusions of the analysis in any substantive way.

The household's problem is to choose the location of its members in order to maximize its expected utility function. I set up the household utility maximization problem as one of income diversification. I use a CARA utility function with pooled income to determine where a household's members will locate.

$$E[U^j] = E[\mu_1(x_1, l_1) + \mu_2(x_2, l_2)] - r(\sigma_1^2 + \sigma_2^2 + 2\rho_{12}\sigma_1\sigma_2) + \varepsilon_i$$

I assume that expected earnings in the away location are greater than the expected earnings in the home location, $\mu_a(x_a, l_a) \geq \mu_h(x_h, l_h)$. I also assume that the variance of earnings in the away location is greater than the variance of earnings in the home location, $\sigma_a \geq \sigma_h$. These assumptions are common in migration problems (e.g., Borjas 1987) and in the data section I will show they hold for most of the households in my empirical setting as well. However, here I use them solely to make the following discussion more tractable, as the model can be extended to cases outside of these assumptions (see Chen, et al., 2003). While on average the data fit the assumptions that earnings and variance of earnings are higher in the migration location, households are observed moving from high to low wage areas or from high to low variance areas. This is not a problem for the framework, but discussion of these possibilities would certainly take away from the simplicity of the discussion without adding much in the way of understanding.

Although the assumptions I make are similar to those in Borjas (1987), the model itself is distinct from his essentially because it is a household problem whereas Borjas (1987) focuses on migration as an individual decision. His view is that the choice of location is a determination of where the potential migrant is going to maximize the return to his skills, given the difference in the distribution in incomes between the home and away locations. This is a typical Roy model with earnings being a function of the mean wage plus an individual shock. I go beyond income maximization by viewing the location choice as one that balances the return to skills with the amount of risk to its income that the household is willing to accept. Within the Roy model setting, we can think of this adding another dimension to the income maximization, that of a location specific shock that affects all individual earnings in a particular location.

Having reduced the number of potential locations to two, the household has just three potential choices: being a nonmigrant household that locates both members in the home location and earns expected utility

$$E[U^0] = 2\mu_h(x, l_h) - \frac{r}{2}(4\sigma_h^2) + \varepsilon_0,$$

being a partial migrant household that locates one member in the home location and one member in the away location and earns expected utility

$$E[U^1] = \mu_{a1}(x, l_{a1}) + \mu_h(x, l_h) - \frac{r}{2}[\sigma_{a1}^2 + \sigma_h^2 + 2\rho_{a1h}\sigma_{a1}\sigma_h] + \varepsilon_1,$$

or being a full migrant household that locates both members in the away location and earns expected utility

$$E[U^{2}] = 2\mu_a(x_a, l_a) - \frac{r}{2}(4\sigma_a^2) + \varepsilon_{\mathrm{a}}.$$

The household will choose the option which provides the highest utility. Recall the above assumptions that expected earnings and the variance of earnings are both higher in the away location than in the home location. Given this, which migration option provides the highest utility is not immediately obvious. A comparison of returns only would place every household in the full migration category. A comparison of the risks only would place nearly all households in either the no migration category or in the partial migration category, depending on the level of correlation between the home and away locations. By combining the risks and the returns of the migration decision in one utility function, the framework encompasses both the risk-taking and insurance seeking behaviors of migration.

Partial household migration represent the insurance seeking behavior of migration and occurs in the risk space where the inequalities $E[U^{1}] > E[U^{0}]$ and $E[U^{1}] > E[U^{2}]$ are satisfied. That is, where

$$\frac{r}{2}[3\sigma_a^2 - \sigma_h^2 - 2\rho\,\sigma_a\,\sigma] > \mu(x, l) - \mu(x, l) > \frac{r}{2}[\sigma_a^2 - 3\sigma_h^2 + 2\rho\,\sigma_a\sigma_h].$$

The easiest effect to discern is that the lower bound of the inequality increases and the upper bound decreases with the correlation in earnings between the home and away location. Therefore, both sides of the inequality are more likely to be satisfied when the correlation in earnings is low between locations. A bit more complicated is how the inequalities are satisfied for various values of the variances in the home and away locations. Both the upper and lower bounds are increasing functions of the variance in the away location and decreasing functions of variance in the home location. I transform the equation one more time to better see the effects of the size of the variances in the home and away locations,

$$\frac{r}{2}\sigma_a^2[3-\frac{\sigma h^2}{\sigma a^2}-2\rho_{ah}\frac{\sigma h}{\sigma a}]>\mu(x,l)-\mu(x,l)>\frac{r}{2}\sigma_a^2[1-3\frac{\sigma h^2}{\sigma a^2}+2\rho_{ah}\frac{\sigma h}{\sigma a}].$$

Both the upper and lower bounds are decreasing functions of the relative size of the variances. If the relative size of the variances is too high, the lower bound is satisfied but the upper bound is not. If the relative size of the variances is too low, the upper bound will be satisfied but the lower bound will not. Therefore, for a given difference in wages, intermediate values of the relative variance of earnings are more likely to satisfy both sides of the inequality than high or low relative values. This means that variance at the home location and variance at the away location can be high (or low) and still give a moderate relative value, as long as σ^2 is not so high as to make the lower bound impossible to satisfy. Thus, insurance seeking behavior in the form of partial migration is not risk-free in this context, but is instead a calculated risk which is taken in order to reduce the overall income risk the household faces.

Nonmigrant and full migrant households occur outside this region. Nonmigrant households occur in the risk space where the inequalities $E[U^0] > E[U^1]$ and $E[U^0] > E[U^2]$ are satisfied. That is, where

$$\mu_a(x, l_a) - \mu_h(x, l_h) < \frac{r}{2}[\sigma_a^2 - 3\sigma_h^2 + 2\rho_{ah}\sigma_a\sigma_h].$$

The above inequality is more likely to be satisfied in the risk space where correlation is relatively high and/or the relative size of the variance of earnings is high. Thus, being a nonmigrant household also has its risk, albeit one that is assumed here to be low relative to that which would be faced in the away location.

Similarly, full migrant households represent the risk-taking behavior of migration and occur in the risk space where the inequalities $E[U^2] > E[U^1]$ and $E[U^2] > E[U^0]$ are satisfied. That is, when

$$\mu_a(x, l_a) - \mu_h(x, l_h) > \frac{r}{2}[3\sigma_a^2 - \sigma_h^2 - 2\rho_{ah}\sigma_a\sigma_h].$$

The above inequality is more likely to be satisfied in the risk space where correlation is again relatively high and/or the relative size of the variance of earnings is low. Above, I assumed that the variance of earnings in the away location is higher than that in the home location. Thus, the full migrant household is facing risks that are higher than if the household had chosen one of the other migration options. The reason that the household will engage in this risk-taking behavior is that the return is high enough to offset the risks the household will face as well as the foregone insurance benefit the household could have gained through partial migration.

3 Empirical Strategy & Data

3.1 Empirical Strategy

The problem of the empirical work is to estimate the likelihood that a particular migration option is chosen given household and community characteristics and a set of risk factors facing the household. Using the utilities U^i as defined in the framework, the household will choose migration option *i* according to the following rule

$$y_i = \begin{cases} 1 & if\ U^i > U^j\ for, j = \{0,1,2\}\ and\ j \neq i, \\ 0 & otherwise. \end{cases}$$

where

$$U^i = \alpha^i + \beta^i W^i + \delta^i \frac{r(\omega_0)}{2} R^i + \varepsilon_i, i = 0, 1, 2$$

and where W^i is the expected wages of the household members and R^i is the set of risk factors facing the household for migration option *i*, as defined in the framework above. Notice that the index function y_i for each choice depends not only the size of the utility derived from that choice, but on the size of the utilities derived from the options not chosen. This explicit interdependence is exactly what we want when estimating the impact of the model parameters on the household migration decision. For example, in just looking at the utility functions for each choice, one may be led to believe that the correlation in incomes between two locations affects only partial household migration. Because the index function depends explicitly on the size of all of the utilities, one does not make this mistake. In addition to the correlation of incomes between two locations, the variance of income in both locations affects the index function of all of the migration choices, thus providing us with a way to empirically test the framework set out above.

By assuming that the ε_i come from a normal distribution with mean zero and variance σ^2, I can use a multinomial probit model to estimate the relationship between the expected wages, the risk factors, and the migration choice made by the household. The multinomial probit model estimates a scaled model that is differenced with respect to one of the alternatives. Here, I choose being a nonmigrant household as the base outcome against which to compare the probabilities of being partial and full migrant households. Thus, the empirical estimation is of the following two differences, dropping the expectation signs in the definition of the new differenced utility:

$$U^{10} = \mu_a(x, l_a) - \mu_h(x, l_h) - \frac{r(\omega_0)}{2}[\sigma_a^2 - 3\sigma_h^2 + 2\rho_{ah}\sigma_a\sigma_h]$$

$$U^{20} = 2(\mu_a(x, l_a) - \mu_h(x, l_h)) - \frac{r(\omega_0)}{2}[4\sigma_a^2 - 4\sigma_h^2]$$

The first portion of each equation consists of factors affecting the expected wages of the household members and takes on the same form in both equations, $\mu_a(x, l_a) - \mu_h(x, l_h)$. Because I do not have direct data on wages in all locations, I could use a set of household and location characteristics to control for the things which are expected to impact the wages household members earn. Household characteristics should act on both wages in the same manner and, thus, should not affect the decision to migrate through the wage mechanism. Therefore, in the basic estimation I do not control for household characteristics. However, household characteristics do work through other channels in the model, the most obvious being the level of risk aversion in the household. Therefore, I do add household characteristics to the basic estimation in order to test whether they add any information to the estimation process. Location characteristics, l, consists of a dummy variable for whether the location is rural, growth in GDP per capita and enrollment rates at the primary, secondary, and tertiary levels for both the home and away locations. The risk portion of the estimating equation consists of the variance in income in both the home and away locations, the correlation of incomes between two locations, and the household's coefficient of risk aversion. To avoid both the omitted variable and reverse causality problems when estimating the probability of the migration decisions, I use historic rainfall patterns to proxy for the risk factors when estimating this equation. In addition, a measure of risk aversion does not exist in the data so I cannot use it in the estimation process. I do, however, test several potential proxies in section 5.1. Thus, the estimating equation for testing the framework is:

$$U^{i0} = \tilde{\alpha}^i + \tilde{\beta}^i L + \tilde{\delta}_1^i \sigma_h^2 + \tilde{\delta}_2^i \sigma_a^2 + \tilde{\delta}_3^i \rho_{ah} \sigma_a \sigma_h$$

Households choose a migration option based upon both the risk and return of the three options, but I focus on the effects of the risk factors in the estimation process because these provide the test of whether the above framework is appropriate for this decision making process. If the framework above is appropriate, then households should shy away from risky migration decisions and opt for safer locations in which to earn income. That is, both partial and full migrant households will be coming from locations with high variance in income at home and going to places with variances in income that aren't too high. In addition, they will be going to locations which do not have perfectly correlated incomes with one another. What this means in terms of the model parameters is that we should find negative impacts of variance in the away location on the probability of being a partial migrant household and on the probability of being a full migrant household. Variance in the home location should have a positive impact on these two probabilities. The correlation between locations has a differential impact depending on which probability is being considered. The probability of being a partial migrant household will be negatively impacted by the correlation between locations, while we expect a zero impact on the probability of being a full migrant household.

In addition to the above variables, we might expect rural and urban households to act differently based upon their access to alternative means of insurance. Households can either self-insure through savings, diversifying income sources, or migrating, or they can find insurance through their networks at the familial, village, or some other level. Rural households tend to have less access to or face higher costs of using alternative means of self-insurance than urban households and we would expect them to seek insurance through migration more often than urban households as a result. Urban households, on the other hand, have likely dissolved some or all of their network ties, and we would expect them to seek insurance through migration more often than rural households for this reason. The question of who uses insurance more is an empirical one. Therefore, I interact the dummy variable for whether the home location is rural with the risk factors in order to control for these possibilities. Since the model focuses on migration, strong network ties may dampen the insurance effect of migration in partial migrant households, but could show up as an insurance effect in full migrant households. That is, covariance might have a muted effect in partial migrant households and a strong effect in full migrant households rather than the other way around.

In section 4, I report the coefficients from four estimation equations based on the estimating equation above. The first is a baseline model which includes only the risk factors and location characteristics. The second adds household characteristics to the baseline model. The third estimation adds in the interaction of the dummy variable for whether the location is rural with the risk factors without household characteristics in order to test whether rural or urban dwellers make different decisions based upon risk. The fourth tests adds household characteristics to this interactive estimation. In section 5.1, I test possible measures of risk aversion.

3.2 Data

In order to estimate the equation discussed above, I use household data from the Indonesian Family Life Survey (Strauss, Beegle, Sikoki, Dwiyanto, Herawati and Witoelar, 2004; Frankenberg and Thomas, 2000), historic rainfall, district level GDP per capita, and district enrollment rates at the primary, secondary, and tertiary levels. The IFLS provides data on household and individual characteristics as well as migration patterns for individuals. A time series of historic rainfall is used to proxy for income variance in and covariance between locations. GDP per capita is used as a proxy for average wages.

The IFLS began collecting data in 1993 in 321 communities in Indonesia, encompassing 7,224 households and over 22,000 individuals. Through three successive waves, in 1997, 2000, and 2007, the IFLS has collected data from the same households, even when those households or individuals within those households, have moved to a new location. The survey collects detailed data on education, marriage, health, relationships within households, and migration. The migration data makes the IFLS particularly useful for the present study. In each wave, individuals were asked about all moves made since the previous wave that lasted longer than six months, with the first wave attempting to record all known moves prior to the survey taking place.

The location of each move is recorded in detail, with village, sub-district, district, and province codes. Using this data, along with information on relationships within the household, I can construct a variable which records who moved and who did not move. In addition, I know whether the migrants moved across provinces or simply moved to a new house within the same village. Using this information, I define a household as an identifiable spouse pair of husband and wife. A partial migrant household is one in which only one of the spouses has a recorded move while the other spouse does not. Typically, the moving spouse is the husband. A full migrant household is one in which both of the spouses have a recorded move in the same year. A nonmigrant household is one in which neither spouse has a recorded move.

The sample includes both temporary and permanent migrants, but not seasonal migrants. The standard migration questions are concerned with moves lasting longer than six months, thus not including the short term seasonal migrations. An additional survey on circular migration was conducted during the third wave, asking about all migrations lasting longer than two months. However, I use only the standard migration questions asked during each wave of the IFLS to determine who moved since these same questions were asked in all of the waves of the data, and therefore use only nonseasonal migrants in the sample.

Almost by definition, partial migrant households will be temporary migrants since they are maintaining a household in the home location. And, across successive waves of the IFLS partial migrant households continue to report that they are located in the home location. However, one must be cautious interpreting this as an indication that partial migrant households are engaging in temporary migration. It may be that at some point in the future the spouse remaining in the home location will join her husband or that the husband is a permanent partial migrant.

Of full migrant households, approximately 37 percent report that they are located in the home location across successive waves of the IFLS. This may indicate that these households returned to the home location and therefore were temporary migrants or it may be that the household is not yet ready to sever its ties the home community.

According to the above definition, about 10% of the sample used in the analysis (3858 couples) moves. In Indonesia in 2005, there were 4 million recent migrants, or about 2% of the population, as measured as migration out of a province within the last 5 years (BPS Indonesia, 2010). In the IFLS provinces, recent migration is about 5% of the population. While I don't have information that will allow me to break that down into partial and full migrants, I can translate my numbers into equivalent migrants. In my sample, 7% of the households are partial migrant and 4% are full migrant. Partial migrant households have one migrant and full migrant households have two, giving a total of 580 migrants in the sample, or 7.5%. This measure is at the district level and those who move across provinces account for 44% of the total number of migrants, or 253 people. Thus, actual recent migration out of IFLS provinces (5%) is larger than the number of people moving across provinces in my sample (3.3%), but smaller than the number moving across districts (7.5%). This makes sense in that I am tracking only a subset of the possible moves that are occurring. For instance, I do not track migration of adult children or the migration of those without an identified spouse.

Since most of the sample does not move, a most likely destination had to be created from the observed migration data. I construct likely destinations using the first wave of the IFLS. I identify spouse pairs in this wave and assign them a move status of nonmigrant, partial migrant, and full migrant households just as I do with the subsequent waves used for analysis. I then use the migration locations of the partial and full migrant households to determine three possible destinations for the non-movers: the most common destination for partial migrant households in the district, the most common destination for full migrant households in the district, and the most common destination overall for both types of migrant households.

In the model, a household is comparing utilities derived from three different options, being a nonmigrant, partial migrant, or full migrant household. In the base analysis, I allow households to view their options for partial and full migration as different locations. I do this by assigning nonmigrant households what I will call their "best option." I define a nonmigrant household's best option as the migration choice (partial or full migration) which would give them the highest utility *had they chosen that option*. The utility which would have been derived from each option is calculated by assigning the nonmigrant household an identifier for both the most common destination for partial migrant households and the most common destination for full migrant households who share the same home location with the nonmigrant household. I then link the data on the risk factors to these nonmigrant households and use the estimating equation to calculate the utility a nonmigrant household would have derived from exercising each option. I then compare these utilities and use the data on the risk factors associated with the option that would have provided the nonmigrant household with the highest utility *had they exercised that option*. Partial migration was the best option for 59% of the nonmigrant households.

It is possible that households do not view their options as different locations based on which type of migration they will choose. Instead, households may view their options as choosing a single destination and then determine whether they will engage in partial or full migration to that destination. In subsequent analysis, I test whether my choice of counterfactual destination is driving the results. To do this, I construct a different counterfactual by assigning the nonmigrant household an identifier for the most common overall destination for both types of migrant households who share the same home location with the nonmigrant household. I then link the data on the risk factors to these nonmigrant households for use in the analysis.

The picture that emerges from the household characteristics in Table 1 is that the different types of households fit the average profiles we would expect of migrants and nonmigrants. On average, nonmigrant households are older, less educated, and less wealthy than both types of migrant households. Full migrant households are the youngest and most educated households on average and also have the highest average wealth index.

Besides the availability of rich migration data, Indonesian households also suit the two person household structure in the framework above. Studies on household structures by Frankenberg and Kuhn (2004) and de Laiglesia and Morrison (2008) provide support for such a household in Indonesia. Frankenberg and Kuhn (2004) find that Indonesian households are much more like the nuclear families found in the USA than those found in other developing countries, in this specific comparison to Bangladesh. De Laiglesia and Morrison (2008) look at a number of facets of households in African and Asian households, including polygamy and extended households. They find that Indonesia has a lower incidence of both of these attributes than the other countries in their study. The data uphold the two person household view as well. Ninety-three percent of the households in my sample have only one married couple in them.

Historical data on rainfall for each province were obtained from the Global Historical Climate Network data base maintained at the National Climatic Data Center under the U.S. Department of Commerce. This data has been previously used in the case of Indonesia by Maccini and Yang (2009) to study the effect of rainfall in childhood on adult outcomes. The data base contains rainfall data for each country in the world, providing rainfall for each month of the year as well as the GPS coordinates for each weather station. Maccini and Yang (2009) aggregate the monthly data and link it to the district of birth for their study. In this study, I aggregate the monthly data to calculate the annual rainfall recorded at each weather station. Using the GPS coordinates, I assigned a district identifier to each weather station. In instances where more than one weather station was located within a district, I took the average annual rainfall among all of the weather stations to assign annual rainfall to a district for a particular year. Using these annual observations, I constructed the variance of rainfall within a district and the covariance of rainfall across districts. Average annual rainfall averages from 1.8 meters in low lying areas to over 6 meters in the mountains of Java (Encyclopedia of the Nations, 2012). While the differences in average rainfall are great, the framework set out in this paper proposes that it is not the level of rainfall in an area but its variance that is the more important factor in determining migration. Looking at the summary statistics in Table 1, the variance of rainfall has a mean around one meter in both the home and destination locations, but varies by type of migrant household. On average, migrant households come from areas with a higher variance in rainfall and migrate to locations with a lower variance in rainfall.

Looking at these averages, the households are distributed in the risk space according to the pattern defined in the framework section. Nonmigrant households come from areas with the least variance and have options with the highest variance and highest correlation between destinations. As with the household characteristics, full migrant households have exactly the opposite risk factors. These households come from areas with the highest variance and go to places with the lowest variance. Partial migrant households fall directly in the middle and go to the lowest correlated areas. However, if we graph the location of households in the risk space (see Graph 1), we see that the different types of households are not located exclusively as predicted by the model. Instead, there is much overlap of the distributions of the three types of households.

GDP per capita and enrollment rates are from Statistics Indonesia. Growth in GDP per capita was calculated over the period for each district. All types of households have destinations with higher GDP per capita than the home location on average. Full migrant households come from locations with the lowest average GDP per capita. Nonmigrant households have the highest level of GDP per capita on average and the lowest growth rate in GDP per capita at home. Partial migrant households come from locations with the highest growth rate in GDP per capita. Destination GDP per capita is highest for full migrant households on average. Partial migrant households go to locations with a slightly lower growth rate and nonmigrant households face the lowest growth rate in GDP per capita in their potential destinations.

Enrollment rates are matched to the year of observation between 1993-1998. All types of households face higher average enrollment rates at their destinations than at the home location. Partial migrant households face the lowest average enrollments rates at both home and destination overall, with the exception of tertiary enrollment rates at home. Nonmigrant households have the highest average enrollment rates in their destination locations, the lowest average tertiary enrollment rates at home, and the highest average primary enrollment rates at home. Full migrant households have the highest secondary and tertiary enrollment rates at home on average.

The framework does not take into account the cost of migration despite the fact that cost of migration is a known obstacle to migration for very poor households. This is only a problem if we do not find an effect of the risk factors on the choice of migration option. But even for those households which have chosen migration, one worry in this study is that cost may be a factor in the choice of location, rather than the other risk factors of migration. If partial migrant and full migrant households are traveling different distances to their destinations, then we might expect that their costs are different and therefore it is the costs, rather than the risks, which are determining their choice of location. That is, if partial migrant households are traveling further than full migrant households, it may be the cost that is prohibiting a full household relocation rather than the desire for insurance through migration. However, the full migrant households are traveling further on average (162.1 km) than partial migrant households (159.9 km) and the average distance traveled is not significantly different from each other (p=0.94).

3.3 Is rainfall a legitimate proxy for income risks?

Indonesia is the world's largest archipelago and lies wholly within the tropical zone. Average rainfall is high and, because of its mountainous terrain, rainfall is also highly variable across the country. While agriculture makes up only 16 percent of GDP, over half of the population depends on it for their livelihood (Kishore, et al, 2000). It is perhaps most obvious that incomes will be correlated with rainfall in agricultural areas. But we do not need to rely on intuition to tell us this. Levine and Yang (2006) explicitly test whether rice output is dependent on rainfall in Indonesia.

Their findings show that rainfall is a good predictor of output even in minor urban areas. The use of the variance and covariance of rainfall is therefore likely a good proxy for income risks.

Levine and Yang (2006) caution against using rainfall for major cities to predict rice output. Dropping major cities presents a problem for this study since nearly 50% of migrant households have a destination of a major city whereas about 1% of nonmigrant households see a major city as a possible destination. Therefore, I investigate whether we can believe that migrant incomes in major cities can be linked to rainfall even though rice output in these same locations cannot.

It is also likely that rainfall will be correlated with incomes of those working in the tourism, construction, and the manufacturing of foodstuffs and other agricultural or forestry related items. Together these categories account for 77% of the jobs held by men who reported an industry code, and 84% of the jobs held by women who reported an industry code. Table 2 shows the industries in which the heads of different types of households report working. As a group, all types of households are represented in (nearly) all of the same industry categories, but with differing distributions of workers. The table shows that migrant households are moving away from agriculture and into manufacturing and retail sectors. Even in migrant households, though, agricultural work is still mainly in the form of agricultural and animal husbandry workers, with some of the full migrant households in forestry work. This holds true even when we look at the reported occupations of those working in major cities. A majority of the workers in manufacturing are in foodstuffs and the garment industry. Community and personal services comprise both government and private sector positions. Private sector positions include teachers, transportation operators, and bookkeepers, to name several. Generally speaking, those in nonmigrant households work as government officials and teachers more often, while those in migrant households often work as transportation operators.

Table 3 shows the results of a simple regression of the variance of GDP on the variance of rainfall. The results show that variance of rainfall is a significant predictor of the variance of GDP. Even when running the regression including only the major cities, variance of rainfall remains a significant predictor of the variance of GDP. These results, along with the aggregate reported industry and occupation codes, provides evidence that rainfall is a good proxy for income risk across all locations.

4 Results

Table 4 reports the estimation coefficients and predicted probabilities from the multinomial probit analysis for four separate equations. The baseline model in column [1] includes only the levels of the risk factors and controls for location characteristics. Each subsequent column adds new variables to the estimation equation. Column [2] adds household characteristics to the baseline model. Column [3] adds interactions of the risk factors with location type to the baseline model. That is, a dummy variable for whether the home location is rural is interacted with the risk factors. Column [4] reports results when adding both household characteristics and interactions between the risk factors and location type.

In the baseline model, the risk factors are statistically significant for both types of migration. A high home variance motivates migration, while a high destination variance and high covariance between home and destination deter migration, regardless of type of household. This suggests that migrants do use migration as a way to avoid risky locations and privilege safer ones. The framework performs well for partial migration, where the risk factors move in the expected directions and are all significant. Home and destination variances move as expected for full migration, but the covariance remains relevant for full migration. This may be due to the fact that risk diversification in Indonesia is performed more within extended families than nuclear ones.

Despite average distance traveled not being significantly different between partial and full migrant households, distance and distance squared are significant across all of the specifications. This bodes well for the framework in that the risk factors are not spuriously measuring the effect of distance. Coming from a rural location is a significant deterrent of all migration. The difference in primary enrollment rates between locations is marginally significant for partial migrant households.

The results in column [2] are very similar to those in the baseline model, but the fit of the model is significantly better when comparing the two models using a likelihood ratio test (see test statistic in Table 4). The main difference between the two estimations is that when household characteristics are added, growth in GDP per capita becomes marginally significant, but the impact of it and enrollment rates increases in magnitude for partial migrant households. Growth in GDP per capita remains insignificant for full migrant households. Primary enrollment rates become marginally significant for full migration and increase in magnitude in column [2]. Coming from a rural location, distance, and distance squared remain significant.

In column [3], I explore whether urban and rural households are responding differently to risk when engaging in migration. Given that our measure of risk is more highly correlated with actual variations for rural than urban households this separation is informative. In addition, differentiating households on their rural/urban location is adding information to our estimation process as indicated in the likelihood ratio test statistic reported in column [3], comparing the baseline model in column [1] with the model in column [3]. This separation of impacts shows that the framework closely describes the behavior of urban households. Partial migrant households in urban areas are deterred by both a high destination variance and a high covariance between locations, showing that they are using partial migration as a risk diversification strategy. Urban households are prompted to fully migrate when home variance is high and deterred from fully migrating when destination variance is high. Covariance between locations is not a significant factor in the decision to fully migrate, showing that full migration is not used for risk diversification by urban households.

Patterns of migration for rural households follow the framework for partial migration. Partial migrant households in rural areas are spurred to migration by high home variances (p=0.000) and deterred by high covariances (p=0.009), while destination variance is insignificant (p=0.17), showing that partial migration is a risk diversification strategy for rural as well as urban households. These same factors are significant for full migration of rural households, high home variances spur full migration (p=0.001), destination variance is insignificant (p=0.74) and negative, and high covariances deter full migration (p=0.005). The significance of the covariance does not follow the predictions of framework. However, this pattern of migration is consistent with the maintenance of ties to networks in the origin community that is often seen in migrant households. It is also consistent with both anthropological observations (Geertz, 1962; Geertz, 2006) and previous economic studies (Ravallion and Dearden, 1988) on Indonesia. This suggests that rural households are also using full migration as risk diversification within a network that is larger than the nuclear household.

When adding household characteristics in column [4], the results again differ very little from those in column [3] in both significance and magnitude. The pattern for growth in GDP per capita and enrollment rates is the same as in column [2]; growth in GDP per capita becomes insignificant and the magnitude of the location characteristics increases in magnitude for both partial and full migrant households . The addition of household characteristics and differentiating households by rural/urban location increases the fit of the model better than just adding either household characteristics or differentiating on rural/urban location, as we see from the likelihood ratio test statistic in column [4]. Thus, the best estimation model to use for the risk relationship based on the likelihood ratio test is column [4].

In order to assess the predictive power of the model, I compare the probability of being a partial migrant or a full migrant household as predicted by the model to the proportion of households in these categories observed in the sample. These variables are reported in Table 4 and subsequent tables as predicted probability and actual probability. Adding household characteristics has mixed effects on the predictive power of the model. The predicted probabilities decrease from about six percent, or two-thirds of the actual probability, to just over four percent, or one half of the actual probability for partial migration, and decrease from near zero to zero for full migration.

Another way we can measure of the predictive power of the model is to look at whether the model would correctly predict a high probability of being a partial migrant household for a household observed to be partial migrant and predict a high probability of being a full migrant household for a household observed to be full migrant. This variable is reported as the percentage of correct predictions in Table 4 and subsequent tables. When we look at how correctly predictions are made by the model, the last specification using both location type interactions and household characteristics does 70 percent better than the next best model for partial migration and 43 percent better for full migrant households. Thus, the model's predictive qualities uphold the use of column [4] to estimate the relationship between risk and migration.

5 Robustness Tests

5.1 Proxies for Risk Aversion

In Table 5, I explore whether certain households characteristics can help distinguish how households respond to risk. We can think of these characteristics as proxies for risk aversion which are observable in the data. Alternatively, rather than reflecting how risk averse a household is, we can think of these characteristics as mechanisms or strategies used to respond to uncertainty just as migration might be. Either way, our expectations on how a household possessing a particular characteristic will respond to more risk remain the same. Thus, the interpretation of the results in Table 5 will not change and I refer to these characteristics as proxies for risk aversion.

I choose four possible measures of risk aversion: a wealth index, landholdings, household size, and education level of the head of household. Table 5 contains the results of the estimation using each of the proxies as well as their predictive ability and likelihood ratio test in comparison to the baseline model. All regressions include household characteristics as in column [2] of Table 4.

To capture overall risk aversion, I first construct a wealth index from the data on asset ownership as outlined in Filmer and Pritchett (2001). To be assured this measure is exogenous to the migration decision, I construct the wealth index from household data recorded in the beginning period, before migration occurs. This avoids the possibility of migration choice affecting the wealth of the households in the sample. However, Filmer and Pritchett (2001) do indicate that their method may have problems when comparing rural and urban households. The problem is that since some assets depend on service provision, such as water and electricity, urban households may appear wealthier than rural households. Since we rely on the wealth index to proxy for risk aversion, this would make urban households less risk averse than rural households by default. In Table 5a, I explore whether this is true by comparing some of the characteristics which are used to construct the wealth index by location type.

The first column of Table 5 reports the coefficients from the estimation using the wealth index. Wealthier households respond less to the home variance than their poor counterparts in both partial and full migration. This is most likely because they are better able to smooth their consumption by either already having diversified income sources through other mechanisms or by dipping into savings. Household use of insurance is not differentiated by wealth, but the use of this proxy does better in the estimation when compared to the baseline model as seen in the significant likelihood ratio statistic.

Since as constructed the wealth index may be creating a bias towards risk aversion in rural areas and may be dampening the effects of this proxy, I report the average wealth index and the proportions of households with certain characteristics by location type in Table 5a. The wealth index is lower on average across rural households versus urban households (p=0.000). And, in general, rural households have lower levels of positive characteristics making up the wealth index than do urban households. However, the inclusion of interactions of rural*wealth index*risk factor in the estimation is rejected in column [4] of Table 6, indicating that this measure of risk aversion is not acting differently based on location type.

The reason for this may be that the characteristics most associated with service provision are sometimes more lacking in urban areas than in rural areas. For example, “waste near the home” is a more common characteristic for rural households as we might expect if there is no provision of waste removal or no common dump site. But, “stagnant water around the home” is more common for urban households, albeit of a low occurrence for all households. In addition, the lower level of the wealth index for rural households is just as likely due to characteristics which have nothing to do with service provision, such as “floors and walls made of durable material” as shown in the table, as it is due to lower levels of service provision.

Landholdings represent accumulated wealth, which may be a better proxy for risk aversion for rural households since it is not dependent on service provision. Households with high levels of landholdings may be better able to finance migration, either because landholdings are associated with higher income or because they afford the household the ability to borrow funds for migration. However, landholdings also represent a tie to the home community, which may deter migration. Because of this ambiguity it is not surprising to find that households are not differentiating themselves according to this risk aversion proxy. The likelihood ratio test using the baseline model as the null hypothesis rejects the use of this variable as a proxy for risk aversion.

Households should be less risk averse as their education level increases. The results on education levels are exactly what we would expect from our risk aversion proxy. Furthermore, the likelihood ratio test statistic indicates an improvement in the fit of the data using this proxy over the baseline model. Less educated households respond more to a high home variance and a high covariance between locations than their more educated counterparts in partial migration, which is exactly what we would expect given our model. Education levels do not differentiate full migrant households along any of the risk factors. Thus, education levels are a good proxy for risk aversion in this setting.

Household size directly affects the costs involved in a full household migration. The larger the household the more risk averse it is likely to be and less able to finance a full household move. Alternatively, the larger the household size, the more likely it is that there are other adults, including adult children, who can migrate instead of the couple themselves. This should dampen the effects of the risk factors. Otherwise, we should see a negative effect of this proxy for risk aversion interacted with the covariance of rainfall between locations and a positive effect of the interaction between this proxy and the variance of rainfall at home for partial migrant households. We should see a negative effect on all the interactions for full migrant households. Like the results for landholdings, size of household does not differentiate the response to any of the risk factors. Not surprisingly, the likelihood ratio statistic rejects the use of this proxy when comparing this model to the baseline model.

The wealth index provides the best fit of the data as indicated by the likelihood ratio test statistics although it does not have the expected effects of a proxy for risk aversion. Only the education level of the head of household has the results for varying levels of risk aversion that we would expect if our model is appropriate, but its rejection level in the likelihood ratio test is lower than for the wealth index. The education level of the head of household does slightly worse (about 3% fewer correct predictions of partial migrant households, same percentage correct for full migrant households) in terms of predictive ability.

Finally, I compare the use of the wealth index with the use of the rural location dummy variable as the interaction term in Table 6 since these two interactions had the highest likelihood ratio test statistics when compared to the baseline model. I do this using two likelihood ratio tests where the alternative model is a "supermodel" containing both interactions. I use two different null hypotheses, one without the rural location interactions and one without the wealth index interactions. Both interactions add significantly to the fit of the model when the other interaction has already been used. Adding the wealth index interactions when rural location interactions are already included in the estimation results in a test statistic of 18.52 (p=0.0001). Adding the rural location interactions when wealth index interactions are already included in the estimation results in a test statistic of 19.56 (p=0.008). Thus, by the likelihood ratio test, the rural location has a higher rejection level and is a better estimator. However, looking at the predictive ability of these two models, the wealth index does 12.5% better at predicting partial migrants, while rural location does 12% better at predicting full migrants. Thus, on the basis of predictive power we might choose to use the wealth index over rural location.

Alternatively, rather than choosing either wealth index interactions or rural location interactions, we could use both interactions in the same model since both interactions add significantly to the model when the other has already been included. In addition, the coefficients on the interaction terms remain largely the same and maintain the same significance. The one exception is rural location interacted with home variance, which becomes insignificant when both rural location and wealth index interactions are included in the estimation in column [3]. Based on predictive power, however, column [3] does less than one percent better than that in column [2] at correctly predicting partial migrants and 12 percent better for full migrants. Column [3] does 13 percent better than column [1] at correctly predicting partial migrants and the same for full migrants. Thus, if we want to use the simplest model possible, we might choose to use only the rural location or wealth index interactions since we do not gain a lot in terms of predictive power when using both interactions.

In column [4] I add a double interaction of rural location and the wealth index interacted with the risk factors (rural*wealth index*risk factor). The double interactions all move in the direction opposite of what is expected, with the rural poor being deterred from migration by a high home variance and spurred to migration by a high destination variance and a high covariance. None of the double interactions are individually significant and the likelihood ratio test weakly (p=.108) rejects the interaction terms in column [4] when compared to the model in column [3] which uses both of the individual interactions of rural location and wealth index, but does not include the double interaction of both. This is not surprising given that the wealth index interaction terms for rural households are jointly insignificant in Table 5. This model, however, does better (9% more correct predictions) at predicting partial migrants than the model in column [1], but slightly worse than column [2] (3% fewer correct predictions).

5.2 Definition of GDP per capita

In Table 4, we used growth in GDP per capita to measure opportunities available in the home and destination locations. Higher growth in the destination pulled migrants away from the home location as expected. This effect was significant in the baseline model, but became insignificant when including household characteristics in the estimation. While the growth in GDP per capita may be the most appropriate measure of opportunities available in a given location, it may not accurately reflect the actual knowledge that households have about either the home or away locations. Instead, households may be aware of how well a location is doing in a given year or how a location does on average. Table 7 reports estimation results when using different measures of GDP per capita in an attempt to recapture the significance of the GDP per capita estimator.

The risk factors remain significant in every estimation and the magnitude of their effects changes very little. Thus, the measure of GDP per capita used is not affecting the estimation with respect to the main part of the estimation. There are differential effects, however, on the GDP per capita estimator itself.

Column [1] contains the results when using growth in GDP per capita in the model including household characteristics. The effect of this measure is positive for both partial and full migration, weakly significant for partial migration, and not significant for full migration. In columns [2]-[4] of Table 7, I use point in time measures of GDP per capita. Only the coefficient for lagged GDP per capita in full migration is both positive and significant and the coefficient for partial migration is insignificant and is of the wrong sign. This result is more in line with what we might expect from migrant households. In other words, partial migrant households are not as concerned as their full migrant counterparts with wage gains. Average GDP per capita and GDP per capita adjusted for household size are significant, but negative in partial migration and insignificant in full migration.

Since households that move are more likely to be driven by the wage portion of the framework than other households, using lagged GDP per capita may make more sense than using the other measures in terms of estimating the effect of opportunities on the household's propensity to be full or partial migrant. However, its use does not have a strong impact on the magnitude of the estimators for the risk factors, whose effect we are concerned with in this paper.

5.3 Home location

In Table 8, I consider two different scenarios associated with the home location which may be affecting the results. First, I consider whether some individuals may have migrated to a new location in order to reduce their risk prior to the sample period. Such a scenario would potentially reduce the need to use further migration for insurance if the household maintains ties to the previous location. Second, I consider whether there may some spurious relationship between locations in Indonesia which is being picked up by the estimation process. Such a scenario would attribute insurance type behavior to migrants between locations when none exists.

One way to test the first scenario, in which households have already migrated to reduce their exposure to risk, is to use birth location instead of current location in the estimation. I use the birth location of the husband, which may or may not be the current location of the household. Because the current location is the same as the birth location for approximately 60 percent of households, the risk factors for birth and current location are correlated. In fact, variance of the birth location is highly correlated (0.73) with the variance of the current location. Therefore, it should not be surprising that variance for the birth location does induce migration for both types of migrant households (Table 8, columns [1] and [3]). The covariance between income in the birth location and the destination is less correlated (0.45) with the covariance between income in the current location and the destination. As such, the effect of covariance on the decision to migrate disappears for both types of households, as we would expect if the current location of those who have already moved was chosen for insurance reasons.

One way to test the second scenario, in which the estimation is picking up spurious relationships between locations, is to use risk factors for locations which have nothing to do with the decision to migrate. I test for spurious relationships by estimating the model with a randomly assigned home location and risk factors. The variance and covariance of the randomly assigned home location shows little correlation with the variance and covariance of the actual home location (-0.023 and 0.183, respectively) so I expect that these new random risk factors should have no significant impact on the decision to migrate. In columns [2] and [4] of Table 8 we see that the effects have disappeared for both the variance in the home location are covariance between locations when using the randomly assigned home location. Thus, I find no reason to think that the estimation process is picking up a spurious relationship between locations in Indonesia.

5.4 Destination choices

5.4.1 Destination choices

I originally assigned nonmigrant households a counterfactual destination based on the best option available to a household. This best option was determined from a utility comparison between the most common partial migrant and most common full migrant destinations. This counterfactual allows households to view different destinations as ideal for the different migration options. In Table 9, I report the results from a different counterfactual destination based upon the most common single destination for a district from any type of household. This counterfactual would correspond to a situation in which households view a single destination as ideal and determine whether to be a partial or full migrant household to that destination.

When using the most common destination, households are responding positively and significantly to a high home variance for full migrant households and negatively and significantly to a high covariance between locations for partial migrant households. These results are similar in sign and significance to those using the best option, but provide a starker contrast in the migration decision process. Partial migrants care about nothing but gaining insurance, while full migrants appear to be fleeing high variances at home. Alternatively, the model using the best option shows households weighing all of the risk factors in their decisions to migrate. These results show that the framework's predictions are supported across these two different definitions of the counterfactual destination.

5.4.2 Are migrant households choosing their best option?

The estimated probabilities of partial and full migration are low compared to the incidence of both in the data, although households are responding to risks in a way predicted by the model. As such, we might ask ourselves, how well can we predict the observed choices of migrant households if we omitted all of the risk factors from the equation? When I make this calculation, not migrating is predicted as the best option for 99 percent of the sample movers. Only two percent of partial migrant households and no full migrant households are predicted to make their observed choice in the absence of the risk factors. Thus, even though the predicted probabilities are low compared to the observed probabilities in the data, I find that the risk factors do add to the ability to predict whether a household would be partial or full migrant.

A second question we might ask is, how well we would expect to predict migrant's observed choices if we assigned a random probability to each outcome? To answer this question, we could predict a household's type based on a simple 1/3 probability for choosing each outcome. In this case, we would expect that we would get the prediction to match the observed choice about 1/3 of the time for both partial and full migrant households. Alternatively, we could use the observed incidence in the data as the probability by which to predict a household's type. Doing so would leave us correctly predicting a partial migrant household's type only eight percent of the time and only four percent of the time correctly predicting a full migrant household's type.

Finally, we might ask whether migrant households are choosing their best option based upon the predictions of the framework? If they do not, then how would they have fared with a different choice? To answer this question, I calculate the utility migrant households receive from their chosen destination and type of migration and compare that to the utility that they would have received had they chosen differently.

First, I compare the utility that a partial (full) migrant household would have received, if they had been a full (partial) migrant household, with the utility they did receive. I assign the household the risk factors associated with the most common destination for the non-chosen migration type. Comparing these utilities, 36 percent of partial migrant households and 64 percent of full migrant households chose their best option. For partial migrant households, this is only slightly better than making a random assignment of the best option based on a simplistic probability of 1/3 for each option. However, for full migrant households, the model does almost twice as well as the simplistic 1/3 probability. Thus, the framework is a better prediction of outcomes than random assignment.

Using these utility comparisons, I attempt to characterize the differences between households who choose their best option and those that do not according to the framework. Partial migrant households which chose their best option traveled 150 kilometers further than those who would have done better if they had been full migrant households. Although this difference is not statistically significant, it may indicate that costs that have not been accounted for in the model are a constraint to optimizing location choices. However, when I compare the utility that these households would have received had they chosen the most common destination for partial migrant households in their district to the utility they actually received, utility from the chosen destination was greater than or equal to this counterfactual utility in all cases. Finally, I used as a comparison, the utility that these households would have received had they been full migrant households in their chosen destination. Eighty percent of these partial migrant households which had not chosen their best option would have done better if they had been full migrant households. This may indicate that some partial migrant households intend to become full migrant households at some future date, but either due to costs or due to "trying out" a location they engage in partial migration initially.

Full migrant households which chose their best option traveled 13 fewer kilometers than those who did not, although this distance is not statistically significant. As with partial migrant households, I then compared the utility they achieved with the utility they would have received had they gone to the most common destination for full migrant households in their district. Fourteen of these households (30 percent) could have done better by going to the most common destination for full migrant households than their chosen destination. As a final comparison, I calculated the utility they would have received if they had been a partial migrant household at their chosen destination. None of the full migrant households would have been better off as partial migrant households at their chosen destination.

6 Conclusion

In this paper I show that the insurance seeking and risk-taking behaviors of migration can be reconciled in one framework. By taking into account both the risks and returns of migration, and recognizing that migration often entails part of the household migrating while part of the household remains in the original location, I develop a testable framework based on income diversification across locations. In this framework each migration option entails risk. This even includes not migrating which we often think of as the “safe” option for households. Not migrating, however, involves a higher level of risk because the household is not taking advantage of the diversification of income brought about by migration. Under the right circumstances, households can mitigate their risk by engaging in partial migration. And, lastly, the least risk averse households will choose to move altogether to take advantage of the income gains of doing so.

This framework fits urban households reasonably well, showing that these households use partial migration as a risk diversification strategy. However, rural households do not follow all of the predictions of the framework, diversifying risk in both partial and full migration, a pattern consistent with the maintenance of ties to the networks in the origin community. The interactions of the risk aversion proxies with the risk factors generate the anticipated results only for less educated households. The use of household size and landholdings to proxy for risk aversion do less well. Whether this is because other factors, such as the availability of adult children for migration in large households, are likely muting the effects of insurance seeking or the model does not capture risk aversion properly for these households is left for further investigation. Wealth also does less well in terms of acting as a proxy for risk aversion, but it is still a significant interaction explaining migration behavior.

It is important to recognize how risk and its interactions with rural location, wealth, and education predict migration. As we better understand how migration decisions are formed, we are better able to address household needs not only with a mind to changing those decisions, but also in better serving the communities in both urban and rural areas that are formed as a result. If households are seeking insurance, then to curb migration we can either address diversification of incomes at home or provide more attractive forms of insurance. This becomes especially important, as climate change is likely to make insurance through migration more important in the coming years. Thus, addressing migration means not only facing the traditional challenges of urbanization but also those challenges arising from climate change.

If households begin to seek more and more insurance as climate change occurs, public services need to be designed to address the needs of the specific migrant community that forms as well as the needs of communities of partial households left behind. These rural communities will likely be composed of the elderly, women, and non-working age children, which will require different services from communities of fully intact households. Many developing countries already face these challenges and will be better able to deal with rising partial migration in the future if they design their public services accordingly.

Figure 1. Distribution across the Risk Space

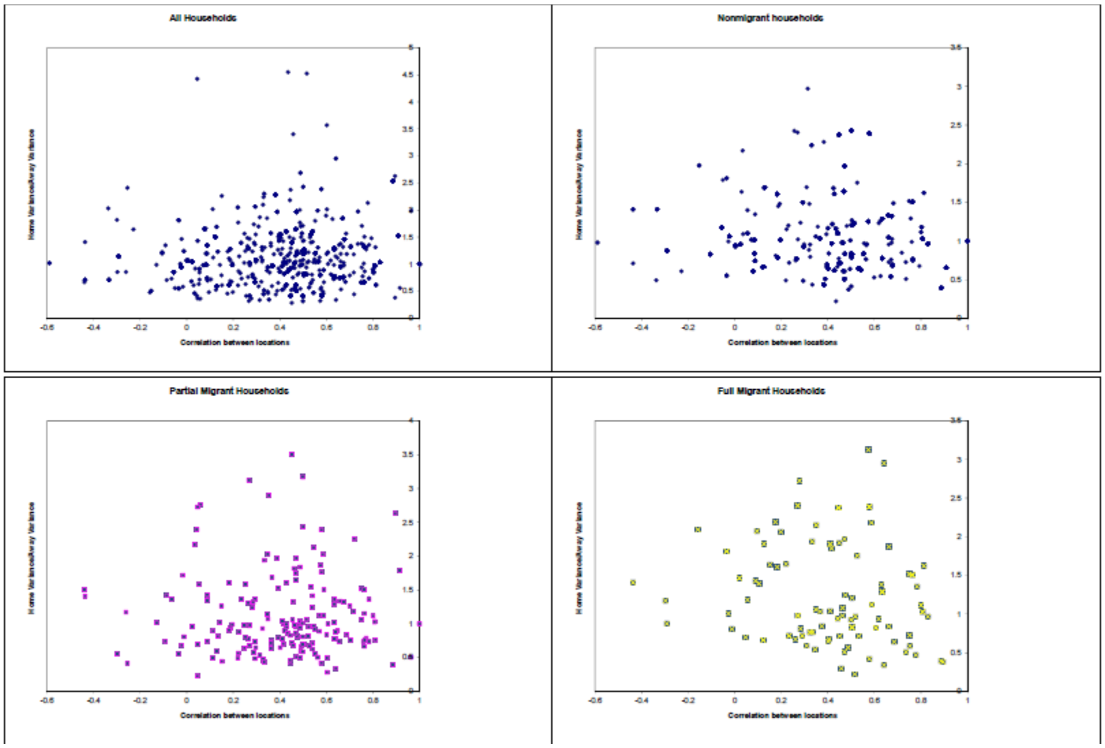

Table 1. Household Characteristics (3858 couples)

	Partial Migrant		Full Migrant		Nonmigrant	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Risk Factors						
Variance At Home (rainfall in meters)	1.10	0.81	1.25	0.95	0.99	0.67
Variance At Destination	1.01	0.71	0.94	0.69	1.11	0.68
Correlation in rainfall between locations	0.40	0.27	0.41	0.26	0.44	0.26
Covariance	0.36	0.35	0.38	0.37	0.43	0.39
Distance to destination (km)	159.90	272.20	162.10	251.60		
Location Characteristics						
Primary enrollment at home	80.25	6.17	80.52	5.57	81.16	6.04
Secondary enrollment at home	38.23	17.55	39.30	17.32	38.83	17.04
Tertiary enrollment at home	7.91	9.85	10.62	14.36	7.37	9.90
Primary enrollment at destination	81.03	5.54	82.14	5.35	82.57	5.65
Secondary enrollment at destination	41.04	16.62	45.66	15.92	46.29	16.42
Tertiary enrollment at destination	11.96	12.04	14.88	12.44	15.65	15.72
GDP per capita at home	3.00	8.27	2.58	3.08	4.26	26.32
GDP per capita at destination	3.42	8.19	4.26	9.28	6.66	41.08
Growth in GDP per capita at home	0.30	0.28	0.29	0.27	0.28	0.29
Growth in GDP per capita at destination	0.29	0.24	0.29	0.30	0.26	0.39
Percent of Rural Origin	43%		41%		54%	
Percent with Rural Destination	61%		56%		91%	
Household Characteristics						
Age of male	33.47	9.75	31.73	6.48	40.06	12.79
Highest grade of male	5.17	1.61	5.55	1.45	4.92	1.79
Age of female	28.66	8.56	27.48	5.89	35.03	11.78
Highest grade of female	5.24	1.61	5.37	1.57	4.77	1.86
Wealth index	10.27	1.30	10.37	1.17	10.15	1.33
Household Size	5.11	2.28	4.52	1.79	4.79	2.03

Table 2. Industry categories for workers by Migration Type, percentage represented*

	Nonmigrant Households	Partial Migrant Households	Full Migrant Households	Households Migrating to Major Cities
Agriculture	34	24	11	19
Manufacturing	13	28	19	29
Construction	14	0	11	9
Wholesale, Retail, Hotels	0	17	21	14
Community and personal services	20	26	27	19

*these percentages are for those reporting an industry which is a subset of the full sample

Table 3. Prediction of GDP variance using Rainfall variance

	Variance of GDP	
	All districts	Major Cities
Variance of Rainfall	31,501.55***	32,831.89***
	(938.208)	(1022.337)
R-square	0.24	0.58

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimation Coefficients from Multinomial Probit

	Partial Migrant Households				Full Migrant Households			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Risk Factors								
Variance of rainfall in home location	0.278***	0.234**	0.0614	0.0203	0.382***	0.353***	0.303**	0.282**
	(0.0904)	(0.0947)	(0.117)	(0.124)	(0.101)	(0.105)	(0.133)	(0.141)
Variance of rainfall in away location	-0.481***	-0.536***	-0.582***	-0.648***	-0.602***	-0.612***	-0.856***	-0.900***
	(0.0739)	(0.0797)	(0.0918)	(0.0983)	(0.105)	(0.108)	(0.164)	(0.170)
Covariance of rainfall	-0.339***	-0.300**	-0.310**	-0.285**	-0.301**	-0.285*	-0.274	-0.289
	(0.111)	(0.120)	(0.123)	(0.134)	(0.142)	(0.150)	(0.175)	(0.186)
Rural*Variance of rainfall in home location			0.502***	0.478***			0.172	0.134
			(0.171)	(0.180)			(0.192)	(0.200)
Rural*Variance of rainfall in away location			0.350*	0.391*			0.794***	0.910***
			(0.192)	(0.204)			(0.236)	(0.247)
Rural* Covariance of rainfall			-0.491	-0.432			-0.800**	-0.738*
			(0.302)	(0.312)			(0.391)	(0.402)
Distance between locations	0.000529**	0.000602***	0.000651***	0.000713***	0.00195***	0.00196***	0.00205***	0.00207***
	(0.000209)	(0.000222)	(0.000217)	(0.000229)	(0.000648)	(0.000696)	(0.000656)	(0.000703)
Distance between locations Squared	-5.74e-08***	-6.40e-08***	-7.28e-08***	-7.78e-08***	-1.11e-06**	-1.16e-06**	-1.07e-06**	-1.11e-06**
	(2.05e-08)	(2.22e-08)	(2.14e-08)	(2.30e-08)	(4.68e-07)	(5.36e-07)	(4.65e-07)	(5.31e-07)
Location Characteristics								
Home location is rural	-0.509***	-0.587***	-1.190***	-1.314***	-0.541***	-0.605***	-1.227***	-1.409***
	(0.137)	(0.148)	(0.274)	(0.294)	(0.161)	(0.175)	(0.328)	(0.349)
Difference in the growth of GDP per capita	0.250	3.515*	0.266	3.207*	0.318	2.048	0.323	2.125
	(0.170)	(1.883)	(0.171)	(1.884)	(0.209)	(2.081)	(0.212)	(2.096)
Difference in primary enrollment rates	0.0334*	0.128*	0.0368**	0.126	0.0312	-0.174*	0.0315	-0.181*
	(0.0170)	(0.0767)	(0.0172)	(0.0769)	(0.0203)	(0.0944)	(0.0206)	(0.0948)
Difference in secondary enrollment rates	-0.00557	-0.0282	-0.0104	-0.0258	0.00365	0.0455	0.000980	0.0473
	(0.00649)	(0.0339)	(0.00675)	(0.0342)	(0.00756)	(0.0383)	(0.00788)	(0.0390)
Difference in tertiary enrollment rates	-0.00251	-0.00580	0.00171	-0.00548	-0.00525	0.0317	-0.000750	0.0353
	(0.00526)	(0.0291)	(0.00572)	(0.0306)	(0.00614)	(0.0277)	(0.00662)	(0.0289)
Year dummies included	X	X	X	X	X	X	X	X
Household Characteristics included		X		X		X		X
Likelihood Ratio Test		103.72***	23.65***	127.44***				
Predicted Probability	6.14	4.4	5.82	4.14	0.0001	0	0.0002	0
Actual Probabilty		8				4		
Percent correct predictions	3.3	8.3	4.7	8	4	4.6	4.6	6.6

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Estimation Coefficients from Multinomial Probit using different measures of risk aversion-demeaned

	Partial Migrant Households				Full Migrant Households			
Risk Factors	Wealth Index	Landholding	Education of Head	Household Size	Wealth Index	Landholding	Education of Head	Household Size
Variance of rainfall in home location	0.243**	0.225**	0.298***	0.239**	0.373***	0.246*	0.382***	0.314***
	(0.0984)	(0.0999)	(0.102)	(0.0958)	(0.109)	(0.142)	(0.113)	(0.112)
Variance of rainfall in away location	-0.566***	-0.522***	-0.569***	-0.526***	-0.623***	-0.537***	-0.627***	-0.615***
	(0.0879)	(0.0823)	(0.0866)	(0.0791)	(0.113)	(0.119)	(0.114)	(0.109)
Covariance of rainfall between home and away locations	-0.277**	-0.324***	-0.412***	-0.305**	-0.259*	-0.409	-0.399**	-0.280*
	(0.124)	(0.124)	(0.148)	(0.121)	(0.154)	(0.266)	(0.182)	(0.153)
Risk Aversion*Variance of rainfall in home location	-0.291***	-0.0105	-0.188***	0.0472	-0.269***	-0.0591	-0.0389	-0.0540
	(0.0750)	(0.0180)	(0.0688)	(0.0421)	(0.0836)	(0.0529)	(0.0777)	(0.0577)
Risk Aversion*Variance of rainfall in away location	-0.00114	0.0135	0.0501	-0.0423	-0.0950	0.0423	0.0187	-0.0181
	(0.0743)	(0.0130)	(0.0579)	(0.0375)	(0.0767)	(0.0312)	(0.0722)	(0.0545)
Risk Aversion* Covariance of rainfall between home and away locations	0.136	-0.00778	0.231**	-0.0189	0.0411	-0.0731	0.183	0.0272
	(0.0970)	(0.0184)	(0.112)	(0.0598)	(0.0945)	(0.120)	(0.137)	(0.0808)
Likelihood Ratio Test	22.67***	5.39	12.24*	4.5				
Predicted Probability	4.3	4.3	4.1	4.4	0	0	0	0
Actual Probabilty		8				4		
Percent correct predictions	9	8.7	8.7	8	5.9	4.6	5.9	4.6

Note: Location characteristics, year dummies, and household characteristics are included in all estimations
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5a. Characteristics used in the Wealth Index by Location Type

	Rural Migrants	Urban Migrants
Average Wealth Index	9.97	10.46
(Std. Dev.)	(1.39)	(1.12)
Waste near home (percent of households)	16.24	9.54
Stagnant water around home (percent of households)	4.1	6.58
Floor or walls of durable structure (percent of households)	92.81	97.85

Table 6. Comparison of Results from using rural and wealth interactions

	Partial Migrant Households				Full Migrant Households			
Risk Factors	Rural	Wealth Index	Rural + Wealth	Rural + Wealth + Rural* Wealth	Rural	Wealth Index	Rural + Wealth	Rural + Wealth + Rural* Wealth
Variance of rainfall in home location	0.0203	0.243**	0.130	0.183	0.282**	0.373***	0.413***	0.472***
	(0.124)	(0.0984)	(0.131)	(0.138)	(0.141)	(0.109)	(0.148)	(0.157)
Variance of rainfall in away location	-0.648***	-0.566***	-0.678***	-0.701***	-0.900***	-0.623***	-0.923***	-0.927***
	(0.0983)	(0.0879)	(0.110)	(0.115)	(0.170)	(0.113)	(0.181)	(0.180)
Covariance of rainfall	-0.285**	-0.277**	-0.273**	-0.289**	-0.289	-0.259*	-0.251	-0.292
	(0.134)	(0.124)	(0.136)	(0.146)	(0.186)	(0.154)	(0.192)	(0.196)
Rural*Variance of rainfall in home location	0.478***		0.259	0.232	0.134		-0.126	-0.149
	(0.180)		(0.198)	(0.198)	(0.200)		(0.223)	(0.224)
Rural*Variance of rainfall in away location	0.391*		0.424**	0.450**	0.910***		0.941***	0.952***
	(0.204)		(0.207)	(0.211)	(0.247)		(0.253)	(0.255)
Rural* Covariance of rainfall	-0.432		-0.408	-0.399	-0.738*		-0.773*	-0.780*
	(0.312)		(0.315)	(0.318)	(0.402)		(0.412)	(0.413)
Wealth*Variance of rainfall in home location		-0.291***	-0.260***	-0.347***		-0.269***	-0.297***	-0.395***
		(0.0750)	(0.0791)	(0.111)		(0.0836)	(0.0899)	(0.132)
Wealth*Variance of rainfall in away location		-0.00114	0.0201	0.0625		-0.0950	-0.0944	-0.0591
		(0.0743)	(0.0825)	(0.0947)		(0.0767)	(0.0952)	(0.108)
Wealth* Covariance of rainfall		0.136	0.119	0.139		0.0411	0.0588	0.149
		(0.0970)	(0.104)	(0.142)		(0.0945)	(0.115)	(0.166)
Rural*Wealth*Variance of rainfall in home location				0.163				0.170
				(0.137)				(0.153)
Rural*Wealth*Variance of rainfall in away location				-0.137				-0.0988
				(0.145)				(0.159)
Rural*Wealth* Covariance of rainfall				0.0263				-0.139
				(0.236)				(0.258)
Likelihood ratio tests:								
Null: rural interactions only			18.52**	20.85*				
Null: wealth interactions only			19.56**	21.9**				
Null: no triple interaction				2.34				
Predicted Probability	4.14	4.3	4.04	4.01	0	0	0	0
Actual Probabilty			8				4	
Percent correct predictions	8	9	9.06	8.7	6.6	5.9	6.6	6.6

Note: Location characteristics, year dummies, and household characteristics are included in
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7. Estimation Coefficients from Multinomial Probit using growth in GDP per capita, Lagged, Average, and GDP adjusted for Household Size

	Partial Migrant Households				Full Migrant Households			
Risk Factors	Growth Over the Period	Lagged One Year	Average	Adjusted for Household Size	Growth Over the Period	Lagged One Year	Average	Adjusted for Household Size
Variance of rainfall in home location	0.234**	0.287***	0.222**	0.222**	0.353***	0.360***	0.342***	0.346***
	(0.0947)	(0.109)	(0.0946)	(0.0945)	(0.105)	(0.119)	(0.105)	(0.105)
Variance of rainfall in away location	-0.536***	-0.502***	-0.520***	-0.513***	-0.612***	-0.599***	-0.620***	-0.618***
	(0.0797)	(0.0843)	(0.0816)	(0.0805)	(0.108)	(0.115)	(0.107)	(0.107)
Covariance of rainfall	-0.300**	-0.349***	-0.311**	-0.317***	-0.285*	-0.268*	-0.263*	-0.268*
	(0.120)	(0.133)	(0.122)	(0.122)	(0.150)	(0.161)	(0.150)	(0.149)
Difference in GDP per capita measurement	3.515*	-0.000870	-0.00961	-0.0732	2.048	0.0124**	0.0139	0.0542
	(1.883)	(0.00598)	(0.0130)	(0.0511)	(2.081)	(0.00520)	(0.0139)	(0.0560)

Note: Location characteristics, year dummies, and household characteristics are included in all estimations
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8. Estimation Coefficients from Multinomial Probit using alternative home locations

	Partial Migrant Households		Full Migrant Households	
	Birth Place	Random Home	Birth Place	Random Home
Risk Factors				
Variance of rainfall in home location	0.252**	0.122	0.342**	-0.117
	(0.121)	(0.534)	(0.121)	(0.669)
Variance of rainfall in away location	-0.664***	-0.553***	-0.779	-0.645***
	(0.138)	(0.081)	(0.154)	(0.106)
Covariance of rainfall	0.165	-0.156	0.322	-0.451
	(0.214)	(0.136)	(0.213)	(0.174)
Location Characteristics included	X	X	X	X
Year dummies included	X	X	X	X

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9. Estimation Coefficients from Multinomial Probit with different counterfactual destinations

	Partial Migrant Households		Full Migrant Households	
	Most Common	Best Destination	Most Common	Best Destination
Risk Factors				
Variance of rainfall in home location	0.0901	0.234**	0.242**	0.353***
	(0.0862)	(0.0947)	(0.0942)	(0.105)
Variance of rainfall in away location	-0.0178	-0.536***	-0.185	-0.612***
	(0.107)	(0.0797)	(0.130)	(0.108)
Covariance of rainfall	-0.478**	-0.300**	-0.390	-0.285*
	(0.213)	(0.120)	(0.245)	(0.150)
Location Characteristics included	X	X	X	X
Year dummies included	X	X	X	X

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 2: Does the Business Cycle Affect Return Migration

1 Introduction

A large body of literature is aimed at tying migration to economic gains for the origin communities. This work has mainly focused on remittances, but a growing literature is tying return migration to development. Early work on international return migration focused on the role of entrepreneurship among returners (e.g., Dustmann and Kirchamp (2002), Dustmann (2003)), but much of the recent work has focused on the return of the highly skilled (e.g., Dustmann, Fadlon, and Weiss (2010); Mayr and Peri (2008)). A single study (Reinhold and Thom (2009)) looks at international returners generally and determines that skill acquisition occurs even among low skill migrants. This is a particularly important finding since migration of low skill workers has not been viewed as a driver of development. In addition, international migration for countries such as Mexico and the Philippines is predominantly low skill and internal migration, which has largely been ignored in this literature, is typically characterized by low skill rural-urban migration. Given that the levels of internal migration are higher and that internal migration is accessible to a larger portion of the population, internal migration is potentially an untapped source of development being overlooked in the discussions linking migration to development.

Within this context, it is important to distinguish between those migrants who are predominantly focused on raising consumption levels of their own household (i.e., consumption-oriented migrants) and those who are focused on making an investment in the origin community (i.e., investment-oriented migrants) since it is this latter type of migrants that will directly affect the development in the origin communities. Previous studies (e.g., Stark, Helmenstein, and Yegorov (1997); Dustmann (2003); Yang (2006); Kirdar (2008)) focus on the return response of international migrants to changes in purchasing power between the host and origin countries to demonstrate the different motivations for migration. In this paper, I show that the response of return migration to GDP per capita can differentiate migrants along the lines of whether they are consumption-oriented or investment-oriented, which is the main contribution of this paper, and my results are consistent with this literature. In addition, I extend the analysis of consumption- versus investment-oriented migrants to internal migration, instead of focusing solely on international migrants as previous studies have done.

Changes in the business cycle should affect both consumption- and investment-oriented migrants by altering their ability to meet their goals, but these effects will be different depending on which goals the migrant is trying to achieve. Thus, given that consumption-oriented migrants should return to origin whenever the marginal benefits of staying at destination fall below the marginal costs and investment-oriented migrants should return to origin when they have met their investment goals in terms of financial, human, or social capital, the return response of migrants to the business cycle at both origin and destination can help us differentiate between these two types of migrants.

Consumption-oriented migrants will be weighing the marginal benefits and costs of staying at the destination. As such, I assume that their response to a boom in the business cycle at the origin location should lead them to return since the marginal benefit of staying at the destination shrinks as the origin economy improves. However, return during a trough in the business cycle means that the purchasing power of their savings increases as the prices at the origin decrease. The former effect will be stronger for younger migrants, who are likely to continue to work upon their return to the origin. The latter effect will be stronger for older migrants who are more likely to retire upon return. Thus, given how we expect responses to vary with age, we may see an increase, a decrease, or no change in the return of consumption-oriented migrants in response to the business cycle at origin depending on the age make-up of the migrant population. In addition to their responses to the business cycle at origin, I assume that increases in income at the destination location should lower the return of consumption-oriented migrants since the marginal benefit of staying at the destination increases as the destination economy improves, reducing the incentive to return to the origin location. I also assume that the effect of the destination economy will vary with age and that its effects should be less strong for those close to or at retirement age.

Alternatively, I assume that an improved economy at origin will make it more likely that investments will be successful and that the household can meet its financial goals for investment without migration. Therefore, investment-oriented migrants should return with a higher probability in response to an increase in income in the origin location. I also assume that investment-oriented migrants will be more likely to return when income in the destination increases since an improved economy makes it more likely they will have met their investment goals. These effects should be smaller or nonexistent for migrants who are investing in human and social capital, since obtaining both require time that is independent of the income level. I assume further that these effects will vary by age and that, because younger migrants have a longer time horizon over which to benefit from an investment, we should find that they are more likely to be investment-oriented.

In this paper I investigate how return migration responds to GDP per capita in the origin and destination locations of migrants from and within Mexico using individual and household data from the National Survey of Rural Mexican Households (ENHRUM) for the period 1993-2002. I choose to study Mexico because of the large amount of both internal and international migration exhibited by Mexicans. This phenomenon is captured in the ENHRUM data through the recording of where an individual worked during any given year during the period used, allowing me to compare the return behavior of migrants according to destination and demonstrate that return from internal migration is a potentially important source of development in origin communities in Mexico.

Although return migration occurs at a single point in time, the panel nature of the data allows me to exploit the variations in the business cycle both across and within individuals. Using the cross-section of the point in time decision to return or remain at destination in the last year of work at the destination, this paper finds that the response of return migration to GDP per capita can differentiate migrants along the lines of whether they are consumption-oriented or investment-oriented.

In the cross-section, GDP per capita appears to have a negative and significant impact on return probability in both the origin and destination locations for international migrants. That is, as expected, migrants from Mexico to the USA are less likely to return to origin when the USA economy is doing well, indicating they are likely to be more consumption-oriented since marginal benefits to staying are rising. They are also less likely to return when the origin economy is doing well. This result is consistent with previous literature (Stark, Helmenstein, and Yegorov (1997); Dustmann (2003)) that finds purchasing power is an important determinant of return migration. In contrast, GDP per capita at origin has a positive impact on return for internal migrants. This positive impact on return from the origin economy could indicate either consumption-oriented return because of a decrease in the marginal benefits of staying at the destination or investment-oriented return to conditions which are ripe for making an investment or which reduced the needs for migration funds to finance the investment. GDP per capita at destinations within Mexico is insignificant, which is what we would expect if internal migrants are more investment-oriented.

Because we cannot control for individual heterogeneity using cross-section techniques, I exploit the panel nature of the work histories to test the robustness of the cross-section findings using a fixed effects framework. The full panel of migrants finds little impact of the business cycle on decisions to return. The sole significant response is that of internal migrants responding negatively to the origin economy. If we take these results by themselves, they would contradict the findings of the cross-section for both sets of migrants. That is, international migrants appear to be investment-oriented and internal migrants appear to be consumption-oriented, although weakly so (p=0.08).

However, there is reason to think that this estimation may lack power since less than five percent of the panel observations are returns, meaning that there is little variation in responses to the business cycle in the data. As such, I re-estimate within the fixed effects framework using only the observations from those who do eventually return, increasing the observed returns to 25 percent of the panel observations. While this limits the ability to extrapolate results to the larger migrant population, it provides a check of whether the non-response of international migrants and weak response of internal migrants is due to lack of observed variation in response to the business cycle or because these are the true responses to changing economic conditions.

Using the panel of returners only, I find that migrants from Mexico to the USA are less likely to return to origin when the US economy is doing well and are unresponsive to the origin economy. Although this is a different result for the response to the origin economy from that of the cross-section, these results do indicate that international migrants from Mexico are more consumption-oriented. I find that internal migrants are unresponsive to both the destination and origin economies using the panel of returners. As with the results for international migrants, this is a different result for the response to the origin economy from that of the cross-section but we would still make the same conclusions, that internal migrants are more investment-oriented.

These results support those of the cross-section, making it likely that the full panel estimation lacks power rather than indicating the true motivations of migrants from and within Mexico. At least for those that return, it appears that internal migrants are more likely to be drivers of development than international migrants from Mexico. While one must be cautious in the interpretation of the results for the larger migrant population, these findings indicate that we should take a closer look at internal migration as driver of development in rural communities.

Using the cross-section data, I further investigate how migrants respond to GDP per capita by interacting GDP per capita with age, marital status, and education. Consistent with expectations, I find evidence that younger migrants are more likely to be investment-oriented than older migrants. Married international migrants are more likely to be consumption-oriented, but married internal migrants are more likely to be investment-oriented. Results from interacting GDP per capita with education reinforce the basic results that international migrants are more likely to be consumption-oriented and internal migrants are more likely to be investment-oriented. In addition, international migrants with lower levels of education have a much stronger consumption-orientation than those with higher levels of education. For internal migrants, it is those migrants with higher levels of education or without a high school diploma who exhibit investment-oriented behavior. Those with no education or middle levels of education have a lack of response to GDP per capita in both locations.

A final test of whether our results remain consistent with expectations is to look at whether current GDP per capita is the correct measure of economic conditions to which migrants respond. One may think that it is GDP per capita in the recent past rather than current GDP per capita that is driving return. Results using two years of lagged GDP per capita do not indicate that this is the case, as the return decisions of both types of migrants do not change with the addition of the lagged GDP per capita measures.

This paper also contributes to the literature tying migration decisions to cyclical fluctuations by extending this type of analysis to return migration. Previous studies on international migration, such as Mayda (2010) and Ortega and Peri (2009), show that international inflows increase when GDP per capita is high at destination, and fall when it is low and that this effect is maintained even when accounting for how restrictive immigration policies are. Ortega and Peri (2009) go further and show that the increase in inflows corresponds to a one for one increase in employment. Simpson and Sparber (2012) breakdown GDP into long run trends and short run fluctuations and show that trends matter at origin and that short run fluctuations matter at destination, i.e., migrants leave economies that are consistently doing worse and gravitate to economies that are doing better now.

Internal migration shows similar patterns in the literature, with migrants tending to go to places doing well and coming from places not doing so well (e.g., Lundborg (1991), Hughes and McCormick (1994), Hunt (2000), Saks and Wozniak (2011)). This literature often finds a paradox with respect to the origin economy. Hunt (2000) shows that wages at origin are actually pushing migrants to other locations. Pissarides and Wadsworth (1989) show this same paradox with respect to the unemployment rate. Both phenomenon are likely explained by ability, or inability, to finance a move.

None of the above studies look at return migration, which is the main contribution of my paper, and my results are consistent with this literature in that GDP per capita at destination, for both internal and international migrants is higher than GDP per capita at origin when measured at the end of a migrant's stay at destination.

The following section distinguishes between consumption and investment-oriented migrants. Section 3 describes the data and estimation, Sections 4 and 5 discuss the results of the estimation process, and Section 6 concludes.

2 Distinction between investment-oriented and consumption-oriented migrants

The literature on return migration focuses on two overarching motivations for migration that later translate into return to the origin location, to increase consumption and to gain capital for investments (Stark, Helmenstein, and Yegorov (1997); Dustmann (2003); Yang (2006); Kirdar (2008)). Consumption-oriented migrants are looking to increase consumption over their (and their household's) lifetime, weighing the marginal benefits and marginal costs of staying at destination in order to determine when to return to origin. Investment-oriented migrants are looking to gain financial, human, or social capital (or some combination of the three) with which to return to their origin and invest.

Consumption-oriented migrants will be strictly comparing the marginal benefits and marginal costs of staying at destination in the current period since their main objective is to increase the consumption of the household. Therefore, consumption-oriented migrants may remain permanently at destination if the marginal benefits of doing so always remain above the marginal costs, may return quickly, or may return after an extended stay at destination, with the duration dependent on when the marginal benefits of staying at destination fall below the marginal costs. Investment-oriented migrants on the other hand will be concerned with whether their investment goals have been achieved and whether now is a good time to make the investment. Investment-oriented migrants are by definition intending to return to origin and the length of their stay at destination is determined by their investment goals and their calculation of when is the appropriate time to make the investment.

The focus of literature on the human capital aspect has tended to be the price commanded in the two locations for the human capital that determines migrations and returns (Dustmann (1997), Borjas and Bratsburg (1996), Mayr and Peri (2008)), showing that a brain drain occurs when the price for human capital abroad is higher and that there is negative selection on skills in returning migrants. However, other studies have shown that there is a wage premium commanded by returning migrants (Co, Gang, and Yun (2000), Lara (2006), Barrett and Goggin (2010)). And a recent study by Dustmann, Fadlon, and Weiss (2011) develops a model in which the intention of going abroad was to gain human capital for use at origin. The above literature on human capital and migration focuses on high skill labor, as do policy efforts by governments and international organizations such as the International Organization on Migration (IOM) to harness high skill migrants for development in the origin country. However, Reinhold and Thom (2009) showed that when migrants from Mexico work in the same occupation or industry during their migration to the USA and after they return to origin they experience a wage premium over those who never migrated, even if they were not involved in high skill labor. Thus, it is not just the highly skilled who are bringing home additional human capital.

Depending on the orientation of the migrant, their response to changing economic conditions may be different. I first discuss how migrants might be expected to respond to changing economic conditions in general and assuming complete separation of consumption and investment-oriented migrants. I then qualify how these responses may be different between international and internal migrants and any complications arising from the co-existence of both types of motivations for migration.

Consumption-oriented migrants will be pulled back to origin as the origin economy does better since the marginal benefit of remaining at destination is reduced.

However, return during a trough in the business cycle at origin means that the purchasing power of their savings increases as the prices at the origin decrease. The former effect will be stronger for younger migrants, who are likely to continue to work upon their return to the origin. Younger returners are likely to experience an increase in income, giving them the ability to purchase more consumption out of their permanent income. The latter effect will be stronger for older migrants who are more likely to retire upon return since a decrease in prices at origin will allow them to purchase more consumption with the savings they have already accumulated. Since this effect will be a temporary one, and if we assume that migrants know that it is temporary, it should not have as strong of an influence on return decisions as the prior effect of an increase in income. Thus, depending on the make-up of the migrant population we may see an increase, a decrease, or no change in the return of consumption-oriented migrants in response to the business cycle in the origin.

The effect of the origin economy on investment-oriented migrants will depend on the type and amount of capital needed for the investment. Migrants who are seeking financial capital might return to origin due to credit being easier to obtain in the good economic climate, because savings at origin have reduced the need for savings from the migrant, or because the migrant was waiting for the opportune moment to return to make the investment. Migrants who are seeking additional skills or social capital will be less affected by this change in economic conditions since gaining human and social capital requires time that is unaffected by the change in the origin economy. Those migrants who are close to the beginning of their acquisition of skills will be unaffected by the origin economy, while those who have been acquiring skills for some time may be induced to return to origin before reaching an optimal skill level if the economy at origin is doing well enough to allow for a few “mistakes” to be made at origin and it is the type of skill that could be honed while doing so. Either way, the migrant will often do better to return to origin and make their investment during a good economic climate than a bad one so that, regardless of the type of capital needed, investment-oriented migrants will likely wait until there are good conditions for investing to return even when they have met their investment goals. Because they have a longer period over which to reap the rewards of their investments, we should find that young migrants are more likely to be investment-oriented and therefore to exhibit positive responses to changes in income in both the origin and destination locations. Thus, depending on the make-up of the migrant population with regards to the type of capital needed, we may see an increase or no change in the return of investment-oriented migrants in response to the business cycle in the origin.

Alternatively, as the destination economy does better, consumption-oriented migrants will be pushed to stay at destination since the marginal benefit of doing so has just increased. This effect will be less strong for those close to or at retirement age.

Just as with respect to the origin economy, the effect of the destination economy on investment-oriented migrants will depend on the type and amount of capital needed for the investment at origin and where the migrant is in the cycle of obtaining that capital. Migrants who are seeking financial capital will be more likely to return to origin during good economic times at destination because they will reach their financial goals faster. Migrants who are seeking additional skills or social capital will be more likely to be able to gain both types of capital during good economic times, but will likely be less responsive to the destination economy since skill acquisition takes time and is not dependent on how well the economy is doing. Because they have a longer period over which to reap the rewards of their investments, we should find that young migrants are more likely to be investment-oriented and therefore to exhibit positive responses to changes in income in the destination. Thus, depending on the make-up of the migrant population with regards to the type of capital needed, we may see an increase or no change in the return of investment-oriented migrants in response to the business cycle in the destination.

In summary, if there is a negative correlation between return migration and GDP per capita the origin or destination economy, then migrants are probably not investment-oriented. If there is a positive or no response to the destination economy then the migrants are likely to be investment-oriented. A positive response or lack of response to the origin economy is ambiguous in discerning whether migrants are consumption or investment-oriented.

In addition to differing in the types of migrants, international and internal migrants may have different capabilities of responding to changing economic conditions. Legal international migrants face the obstacle of obtaining a work visa in order to migrate to the USA when conditions are favorable. When migrating illegally, international migrants face the dangers of an attempt to cross the border undetected and may incur huge financial costs in order to do so. Once successful in making their migration, international migrants may be reluctant to return to origin even when conditions are favorable for doing so, dampening the impact of changes in the business cycle in both locations. If this is true, we will be more likely to find insignificant results for international migrants with regards to both the origin and destination economies regardless of whether they are consumption or investment-oriented. The same should not be true for internal migrants since their movements will be restricted only by the affordability of the move.

Secondly, consumption and investment goals are not likely to exist in isolation. For instance, a consumption-oriented migrant might gain additional skills while increasing the consumption possibilities of his household. By doing so, the consumption-oriented migrant is decreasing his marginal benefit of staying at destination, since gaining human capital increases his income possibilities at origin, and making him more sensitive to changing economic conditions at both origin and destination. As a result, the correlation between the return probability and conditions in the origin economy will be more ambiguous since an improvement in the origin economy will further reduce the marginal benefit of staying at destination and induce more return migration than would have been observed without the increased human capital. The response to better conditions in the destination economy will likely remain unchanged in this scenario since the main goal is consumption and the marginal benefit of staying rises with an improvement in the destination economy.

The response to a downturn in the destination economy will likely be stronger since the marginal benefit is shrinking even more from its already lowered level due to the human capital accumulation. Thus, overall, we should see more return migration than we would expect without investment goals.

3 Data and Estimation

In order to estimate the probability of return I use household data from the Mexican National Rural Household Survey during 1992-2002, GDP data from the Bureau of Economic Analysis for the USA and from the Instituto Nacional de Estatistica y Geografia (INEGI) for Mexico, a governance indicator from Transperencia Mexicana, and distance data using Google Maps. The ENHRUM provides data on household and community characteristics as well as migration information for individuals. GDP per capita and unemployment data were used to determine the business cycle effects.

The Mexican National Rural Household Survey (ENHRUM) is a recall based survey of 80 rural communities in 14 of 32 states in Mexico. The communities selected have between 500 and 2500 inhabitants and are a nationally representative survey. A total of 8520 individuals comprising 1765 households were surveyed. In addition to the typical socioeconomic data collected in most surveys, the ENHRUM has data on labor histories for 1980-2002. These labor histories are particularly important for the study at hand because they record for each year of work where the individual was working, either locally, in another part of Mexico, or in the United

States. This allows me to determine whether individuals in the survey migrated, which migrants engaged in seasonal migration, and whether and when each migrant returned or stopped working. The labor histories give me a panel of migrant data by which to test whether the return behavior of migrants can help us discern the motivations of migrants. They also allow me to separate out seasonal migrants, whose return may or may not be related to their consumption- or investment-orientation. This data is used in the estimations both as an enriched cross-section since all of the socioeconomic data come from 2002 and as a panel in a fixed effects framework.

My sample contains individuals between the ages of 16 and 85 who have ever migrated. The youngest migrant in the ENHRUM data is 12. Because of the likelihood that anyone so young migrated to be with family rather than to work, I choose only those over the age of 15. In addition, I select a cutoff of age 85 so that we only capture migrants who might have worked at least one year during the survey. Since I am interested in estimating the probability of return, I cannot use anyone who has never migrated.

Seasonal migrants make up a large portion of workers migrating to the US. These individuals appear in the data as individuals who have intermittent episodes of working in more than one location during the year. For international migrants, these will include working in the US and working in Mexico, either at origin or in some other location, during the same year. For internal migrants, these will include working at another location in Mexico and working at origin. In order to capture this migrant characteristic, I add up the number of times a migrant went to their destination and then returned, either to Mexico generally for international migrants or to origin for internal migrants. If they return at least two times, I count them as a seasonal migrant. Seasonal migrants make up about one-third of the sample (32 percent of international and 28 percent of internal migrants).

Seasonal migrants work in both agriculture and other paid employment in similar proportions to nonseasonal migrants engaging in the same type of migration. Seasonal and nonseasonal internal migrants are similarly involved in independent work (4.6 percent and 5 percent, respectively), but nonseasonal internal migrants are almost all involved in independent work outside of agriculture while seasonal internal migrants are evenly divided between independent work in and outside of agriculture. Still, there may be reason to think that there are unobservable differences between these two types of migrants and I exclude seasonal migrants from the estimation, reducing the sample to 358 international and 415 internal migrants.

Table 1 contains variable descriptions and descriptive statistics for all individuals in the panel. Table 2 contains descriptive statistics for individuals by migrant destination. Differences between international and internal migrants will be touched upon in this section, but discussed in more detail below.

I use the recorded state of the household as the origin location. For internal migrants, I use the Mexican state in which the migrant last reported working between 1993 and 2002 as the destination location. For international migrants, I use the US state in which the migrant last reported working during this same period as the destination location. These locations are fixed throughout the analysis. To determine whether a migrant is returned and when the return occurred, I begin with the last recorded year of work. If the migrant reports working at the destination in his last recorded year of work, then he is not a return migrant and is assigned a return indicator of zero for all years of work as a migrant. Migrants who are still working in 2002 and have not returned are also assigned a return indicator of zero for all years of work as a migrant.

If the migrant reports working at the origin in the last recorded year of work, then he is a return migrant. I then look at the location in the second to last year of work. If the migrant reports working at origin in the second to last year of work, then I look at the third to last year, working backwards year by year until I find the year in which he last worked at the destination location. The year in which the migrant last reports working at the destination location is the return year. The migrant is assigned a return indicator of one in the return year and is assigned a return indicator of zero in all other years of work as a migrant.

The panel is made up of 32 percent return migrants; 26 percent of international migrants have returned and 35 percent of internal migrants have returned. 95 percent of observations at the person-year level are zeroes or non-return years. Fifty five percent are female and the average age is 35. Migrants have 1.65 children on average and 57 percent are married.

Distance traveled is commonly used as a proxy for the costs of migration. Distance traveled is a measure of the distance between the capital of the origin state for the migrant and the capital of the destination state, either in Mexico or the USA. International distances were obtained by plotting location using Google Maps. Distance within Mexico was obtained from the website Mexico Channel (www.mexicochannel.net). On average, migrants are traveling 110 kilometers to their destination, with internal migrants traveling further than international migrants.

Border state is a dummy variable indicating whether a Mexican state lies along the Mexico-USA border. This variable should have differential impacts on internal and international migrants. First, it reduces the cost of migrating to the US both because it reduces the distance necessary to travel to the US, but also reduces the costs of returning to origin or visiting. In addition, these areas are likely more familiar with US culture and thus the cost of assimilation will be reduced. Second, because of "border industries" existing in these states, there will be greater pull to return to them from elsewhere in Mexico, especially after the implementation of NAFTA, which saw a boom in these and other new industries. Twenty one percent of migrants are from border states, but these are mostly international migrants (31 percent) rather than internal migrants (12 percent).

Education measures formal schooling obtained, while skills are actual activities one can perform with some degree of competence. In practice we often freely use the term low skill job to mean a job which does not require any formal education. However, we have no way to account for this in the data, which is why education is often used as a proxy for skills. Formal education is measured in the ENHRUM by asking the interviewee what level of schooling was obtained. This formal schooling includes technical education and holding a commercial license as one category and is the only measure in the data indicating that a migrant has a skill. This is an important distinction since, as I will show in this paper, those with measured skills do not return from an international migration, but have similar internal return behavior to migrants with other measured levels of education. This may lead one to wonder if unmeasured skills do not explain the return behavior of other migrants as well.

The ENHRUM categorizes education into eight levels: no education, preschool, primary education, secondary education, high school graduate, technical degree or commercial license, college graduate, and graduate degree. There are no migrants who have a graduate degree and very few with preschool. Nearly 60 percent of both types of migrants have only a primary education and approximately 20 percent have only a secondary education without receiving a diploma. Another 12 percent have either no education at all or attended preschool. Four percent of international and six percent of internal migrants received a secondary diploma. Two percent of international and 2.53 percent of internal migrants hold a technical degree or have a commercial license. The only significant difference in education between the two types of migrants is being a college graduate; 3.25 percent of international and 1.52 percent of internal migrants have a college degree.

Many of the jobs migrants take in the USA do not require any formal education, but some do require some level of skill, such as maintenance work or customer service requiring bilingualism, for instance. Despite the preconception that migrants from Mexico enter low skill agricultural jobs in the USA, approximately 20 percent of the migrants to the USA in the data report working in agriculture, whereas the other 80 percent report working in some other type of salaried job, regardless of education level. Unfortunately, the ENHRUM does not break the category of other salaried work down further, so it is not possible to determine in which other sectors migrants are working.

Internal migrants report working in agriculture to a lesser degree than international migrants and a small percentage of them are working independently rather than for wages. Internal migrants report working in agriculture only 6 percent of the time, and 89 percent report working in another type of salaried job. While the proportions did not vary much by education level for international migrants, they do for internal migrants. That is, those internal migrants who are high school graduates or have some additional education level are working strictly in non-agricultural sectors. The other 5 percent report working in some independent venture, either agriculture (one percent) or other type of work (4 percent) and it is those with less than a high school degree who are doing so.

GDP data come from the Bureau of Economic Analysis (BEA) for the USA and from the Instituto Nacional de Estatistica y Geografia (INEGI) for Mexico and are measured at the state level in thousands of US dollars. In Table 2, I report both the means for GDP per capita observed in either the year of return for those who have returned or the last year of observed work for those who have not and means at the person-year level. Both sets of measures are similar to one another, with GDP per capita at origin and destination higher for internal migrants than for international migrants. I investigate these differences in more detail in the following subsections.

I construct a wealth index from the data on asset ownership as outlined in Filmer and Pritchett (2001). Average wealth is near to five on a 10 point scale by construction. Households with an international migrant have average wealth closer to six on the scale and households with an internal migrant have average wealth closer to four on the scale.

The good governance indicator comes from an index of corruption and good governance created by Transperencia Mexicana, the local office of Transparency International. TM surveyed residents in each state of Mexico on both actual experience with corruption in government services and business practices and the perception of the existence of corruption. Each category of corruption and good governance was assigned a governance indicator and an overall good governance and corruption index was calculated. The overall good governance and corruption index number was used in the analysis. The average good governance indicator for the sample is 9.6.

3.1 Differential characteristics of internal and international migrants

The main difference between international and internal migration is the crossing of borders. This inherently makes international migration more costly, regardless of distance traveled. Even in this age of technology, there is less contact with origin (at a minimum it is not as easy to return to origin for a weekend or a holiday) and the migrant must integrate into a new culture and often operate in a new language. Internal migration, while involving no border crossings, can involve long distances which are costly, but less so than crossing borders. Contact with the origin location can be maintained with a fair bit of ease, traveling to origin for holidays and weekends when close enough. Migrants do not need to integrate into a new culture or learn a new language (typically). These differences are likely to lead to different characteristics being possessed by the different types of migrants.

Table 2 contains descriptive statistics of non-seasonal individual migrant characteristics by destination (USA and within Mexico). International and internal migrants are not different from one another by measures traditionally used in studies of return migration, i.e., age, marital status, and number of children. Females, however, comprise a larger portion of international migrants than internal ($p=0.02$). International and internal migrants travel similar distances, but 23 percent more international migrants are from border states ($p=0.00$). Given this, it is likely that distance does not capture costs of migration as well for international migrants as it does for internal migrants. The simple fact of crossing the border increases the costs of an otherwise similarly distant migration within Mexico. In addition, the issue of assimilation into a new culture and learning a new language cannot be captured in this traditional measure of migration costs.

Thus, while internal migration is not costless, the cost is more easily overcome, even for poorer families. As these costs increase, we expect to find poorer migrants staying closer to origin and wealthier migrants traveling further and being more likely to be international migrants. International migrants are wealthier than internal migrants, by 1.5 index points and this difference is statistically significant (p=0.00).

There are twice (0.02 more) as many college graduates among international migrants as internal migrants and this is the only statistically significant difference (p=0.098) within the education variables, although it is weakly so. These results are a little surprising since we typically think of the USA as attracting migrants from Mexico with low education levels, but while those with lower education levels make up the bulk of migrants in the sample they are not the only ones. In fact, Chiquiar and Hanson (2005) show that migrants from Mexico to the USA tend to fall in the middle of the wage distribution rather than being at the very bottom.

Typically when looking at migration motivations we look at the economic conditions at or just prior to migration. However, in order to distinguish consumption-oriented from investment-oriented migrants we are looking at return behavior and therefore need to focus on the economic conditions during migration and at the point they are last observed to work at the destination. Because the sample of migrants is made up of both returners and non-returners and those who have yet to make a final return decision, the average economic conditions across all migrants are less informative than if we compare the economic conditions faced by the different categories of migrants (internal, international, returners, non-returners) as well as considering these comparisons look across time. I first look at the differences between the GDP per capita at home and at destination of internal and international migrants in Table 2 and examine the differences in more detail in the next subsection.

Internal migrants faced better economic conditions when returning from a migration as measured in their last year of work at destination, both at origin and at their destination than international migrants. This could mean that internal migrants come from and migrate to locations with higher levels of GDP per capita, which is consistent with the fact that GDP per capita across all of the years is higher for internal migrants on average as shown in the table. It is also consistent with the fact that GDP per capita is higher in all years of the panel for the destination and is higher in all but 3 of the years for GDP per capita at origin for internal migrants (not shown in the table). But, if we consider just the observations of the return year, it could mean that internal migrants choose to return in better economic years than international migrants. If we assume that as measured the difference in GDP per capita at origin and destination captures the relative size of the gains from migration, one can also look at the differences in this gain that international versus internal migrants experience for each year of migration on average.

International migrants have lower levels of GDP per capita at both origin and destination and experience smaller gains in GDP per capita ($2.91) than internal migrants ($7.85) (p-value of difference=0.005). This may indicate that something other than consumption may be motivating international migrants given that the average length of stay at destination is not statistically different (p-value=0.18) between international (9 years) and internal (11 years) return migrants.[1] Several possible motivations exist including high unemployment rates in the origin location, insurance-seeking on the part of the household, or, as will be discussed below, poor governance in the origin.

By definition, investment-oriented migrants want to spend some of their working life at the origin benefiting from their investment and we might expect that this would lead to shorter durations at destination when compared to consumption-oriented migrants. In the data, the difference in duration of migration between international and internal migrants staying longer than one year at destination is insignificant. Thus, responses to GDP per capita at the origin and destination locations becomes even more important in helping us to discern the consumption

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[1] The average length of stay at destination was calculated for migrants staying more than one year at destination since short stays at destination may indicate that the migrant returned because of failure rather than for either investment or consumption reasons. When including migrants with only one year at destination, the difference in duration between international (7 years) and internal (8 years) migrants becomes statistically significant (p-value=0.08).

versus investment orientation of migrants. But even though the duration of migration is insignificantly different, the return on investment from migrating internally versus internationally is \$4.94 for every year of migration or \$49.40 for the average length of stay of 10 years. That is, internal migrants have earned on average \$49,000 more than their international counterparts, a nontrivial difference for anyone, but especially for a rural migrant in Mexico.

In addition to how the economy is doing, it is important to look at the broader environment in which one operates either as a worker or employer or in an independent business. As such, how well governed an area is may be either a strong push to migrate, in areas which are poorly governed, or a strong pull to come back to origin once the migration goals have been achieved, in areas with good governance. International migrants come from more poorly governed areas than internal migrants and the difference between their average good governance index scores (-3.51) is statistically significant (p=0.00).

3.2 Differential characteristics in and between migrants

Table 3 shows characteristics of returners and non-returners for both USA and Mexico migration. USA returners and non-returners are different from each other along three dimensions: the proportion of college graduates, the level of GDP per capita at origin, and the level of GDP per capita at destination. They are not different from each other along the other observable characteristics, including those measures traditionally used in studies of return migration (age, marital status, and number of children).

All college graduates in the sample stayed at their international destination. GDP per capita is lower on average at both the origin and destination locations for returners from the USA than non-returners in their last observed year of work and on average across all of the years. Unlike the patterns for migrants overall, the differences in GDP per capita at origin for international returners and non-returners are insignificantly different in all but two of the years (1998 and 2001), but in those two years GDP per capita at origin is higher for non-returners. The same is true for destination GDP per capita, although in one of the years GDP per capita at destination is higher for returners (1996) and in the other (2000) it is higher for non-returners.

If returners are more consumption-oriented then the relative size of GDP per capita in the origin and destination potentially pushed the marginal benefit of migrating lower than the marginal costs for those who returned. Moreover, given that returners face lower GDP per capita at origin, they have a higher marginal consumption incentive than non-returners if we assume diminishing marginal utility of consumption. On the other hand, the lower GDP per capita at destination and smaller difference between the two, indicate that something in addition to consumption may be pushing returners towards the destination, such as unemployment rates or insurance-seeking on the part of the household.

The statistically significant differences are greater between Mexico returners and non-returners. Returners and non-returners look similar in terms of age, marital status and number of children, but returners tend to be female. The proportion of returners with no schooling is lower than the proportion of non-returners with no schooling. The proportion of returners with only a primary education is higher. The proportions in the other education categories are similar for returners and non-returners.

Returners from within Mexico travel significantly fewer kilometers than non-returners, thus it may be costs that allow return migration versus ties to the community pulling migrants back to origin. Being from a border area is not different between the groups for internal migrants. Returners tend to go back to locations with better governance.

In contrast to international migrants, returners from within Mexico returned to higher GDP per capita at origin than non-returners faced in their last observed year of work and the difference is statistically significant. On average across the years, the differences in GDP per capita at origin are insignificant, but for several of the years (1995, 1997, 1998) the GDP per capita at origin is higher for returners than non-returners. These differences indicate that internal returners have a smaller consumption incentive than internal non-returners if we assume diminishing marginal utility of consumption. Even so, given that GDP per capita at origin is measured in the year of return, the relative size of the positive economic conditions potentially pushed the marginal benefit of migrating lower than the marginal costs. If, however, returners are more likely to be investment-oriented then the home economy was ripe for investing or decreased the need for capital from migration.

The difference in GDP per capita at destination between returners and non-returners is not statistically significant in the last year of work at destination nor across all of the years on average. It is statistically significantly higher in three of the years (1995, 1997, 1999) for returners and statistically significantly higher in 2002 for non-returners. This may indicate that internal migrants are investment-oriented if this translates into insignificant effects of GDP per capita at destination on the return decision of internal migrants.

The difference between Mexico returners and US returners are found in Table 4. US returners are approximately four years older than Mexico returners. Nineteen percent more of returners from the USA are from border states. This is unsurprising since these percentage differences are only slightly smaller than the differences between these characteristics for USA and Mexico migrants as a whole. USA returners are comprised of ten percent more with no schooling, but have otherwise similar levels of education to Mexico returners.

Returners from other locations within Mexico faced better economic conditions both at origin and at destination in the year of their return than returners from the USA. The same is true across all of the years on average. Comparing returners in each year, economic conditions were better at origin for internal returners than they were for international returners in three years (1995, 1997, 1998).

Economic conditions at destination were better for internal returners in two years (1995, 1999) than they were for international returners. Given that internal returners also face better economic conditions than internal non-returners while international returners face worse economic conditions than international non-returners, these comparisons indicate that, of the two types of returners, we are more likely to find in the empirical estimation that internal returners are investment-oriented than we are to find those returning from the USA are investment-oriented.

This indication that internal returners are more likely to be investment-oriented is born out, although to a lesser degree, if we also do a year by year comparison of the age of returners. Recall that we expect investment-oriented migrants to be younger than consumption-oriented migrants because they will have a longer time horizon over which to reap the benefits of their investment. Table 4 shows that in the year of return internal returners are younger than those returning from the USA. When making year by year comparisons of the age of the two types of returners, in six of the years internal returners are older and in three the difference in ages are statistically significant. In the rest of the years age is insignificantly different between the two groups.

Returners from the USA tend to be wealthier and from more poorly governed areas. None of these are surprising since migrants to the USA as a whole are also wealthier and from more poorly governed areas than migrants within Mexico.

Table 4 also contains differences in non-returners from each location. USA non-returners tend to be female, but are not different along age, marital status, or number of children. Twenty-four percent more of non-returners from the USA are from border states, a larger difference than between returners from each destination. USA non-returners have similar levels of education overall to Mexico non-returners, but the difference in college graduates (0.04) is significant.

Similarly to returners, non-returners from other locations within Mexico faced better economic conditions both at origin and at destination in their last observed year of work, across all of the years on average, and for each year individually, than non-returners from the USA. In year by year comparisons of age, international and internal non-returners are virtually identical both in terms of statistically insignificant differences and size of the difference. There is less than 1.5 years difference in age of non-returners in any given year, with most years having less than one year difference in age of non-returners. Taken together with the comparisons of returners from the different destinations, the comparisons of economic conditions facing non-returners tell us that differences in non-returners are driving the differences between the two types of migrants. While this does not negate the differences between returners from the different destinations, it does indicate that internal non-returners are also likely to be a valuable source of development through remittances.

Non-returners from the USA tend to be wealthier and from more poorly governed areas than non-returners from within Mexico, just as returners differ.

3.3 Empirical Estimation

In Section 2, I showed how a migrant's response to the business cycle in the origin and destination locations can differentiate between a migrant who is consumption-oriented and a migrant who is investment-oriented. A negative response to the origin or destination business cycle will indicate that migrants are consumption-oriented. A positive or no response to the destination business cycle will indicate that migrants are investment-oriented. Thus, the goal of the empirical estimation is to determine whether migrants respond positively, negatively, or not at all to the business cycle both at the origin and destination locations.

Since many of the variables which should be or could be time varying, such as wealth and marital status, are measured only in 2002 in the ENHRUM, I first use the data as an enriched cross-section in which each migrant has one observation in either their year of return or their last observed year of work. Defining R^i as the probability that a migrant will return, I estimate the following equation via a linear probability model using OLS:

$$R^i = \beta_0 + \beta_1 X_i + \delta_1 pcgdp_o + \delta_2 pcgdp_d + \varepsilon_i$$

where X_i is a set of migrant characteristics consisting of gender, age, education, marital status, number of children, wealth, and distance traveled, whether the migrant's origin community is located in a border state, and a good governance indicator for the origin state. I include interactions of gender and education and interactions of good governance and education as well. $pcgdp$ is the per capita

GDP in the relevant location, PPP-adjusted in 1993 US dollars, measured either in the year of return, for those who have returned, or in the last observed year of work for those who have not.

A hazard of using OLS is that we cannot control for omitted variables. If unobserved differences cause migrants to choose locations which are at different points in the business cycle, then this choice may bias the impact in the cross-section. And this bias may be exaggerated if the unobserved characteristic is associated with a particular migrant type. Since the data forms a panel I also estimate a fixed effects model to control for unobserved heterogeneity across individuals and test whether the OLS estimation is causing me to draw erroneous conclusions. Using the panel nature of the data, I estimate the probability that the migrant will return R^i with the following fixed effects equation:

$$R^i = \alpha_i + \beta X_{it} + \delta_1 pcgdp_{it}^o + \delta_2 pcgdp_{it}^d + \varepsilon_{it} \ ,$$

Where $\alpha_i$is the individual fixed effect, X_{it} is a set of time varying migrant characteristics, $pcgdp_{it}$ is the per capita GDP in the relevant location, PPP-adjusted in 1993 US dollars, measured in the associated migration year. In the case of the ENHRUM, X_{it} is composed solely of age in the estimation. This is an unbalanced panel with an observation at the person-year level for each migrant in each year of migration.

δ_1 and δ_2 are the coefficients of interest in both equations. If migrants are predominantly consumption-oriented, then $\delta_2 < 0$ and δ_1 can take on any value. If migrants are predominantly investment-oriented, then $\delta_2 \geq 0$ and $\delta_1 \geq 0$. Thus, the sign of δ_2 is a definitive indication of the consumption or investment orientation of migrants and the sign of δ_1 may indicate the consumption orientation of migrants or it may be ambiguous. Using the fixed effects model, I will test whether responses to the business cycle by the same individual are consistent with my claims in Section 2. Using the linear probability model, I will test whether responses between individuals measured in their last year of work are consistent with these same claims.

4 Results

The estimation results are contained in Tables 5-7. Table 5 contains the results of the OLS estimation using one observation per migrant from either the return year for returners or the last year of observed work for non-returners. Table 6 contains the results of the fixed effects estimation for the full panel. And Table 7 contains the results of the fixed effects estimation using only returners. In each table, Column 1 shows the coefficients for migrants to the USA. Column 2 contains the coefficients for internal migrants. Column 3 contains the differences between the coefficients of the two groups.

In the OLS estimation (Table 5) international migrants are less likely to return to origin in response to high GDP per capita in both the origin and destination locations, indicating they are more consumption-oriented since only consumption-oriented migrants have negative responses to GDP per capita fluctuations. In contrast, GDP per capita in the origin location has a positive impact on return for internal migrants. This positive impact on return from the origin economy is ambiguous in determining whether consumption or investment orientations dominate among internal migrants. However, GDP per capita at destinations within Mexico has an insignificant impact on internal return migration and this is what we would expect if internal migrants are more investment-oriented.

In the OLS estimation, age has a positive influence on return of international migrants consistent with expectations. But, age has a negative influence on the return of internal migrants which is inconsistent with our expectations of return behavior since we usually think of individuals migrating when they are young and returning when they are older. This may be an indication that we need to revise this expectation based on type of migration. Alternatively, it may indicate that omitted variable bias is attenuating the effects of age and/or other variables in the OLS estimation. Thus, we should be cautious in drawing conclusions based solely on the OLS estimations. For this reason, in Tables 6 and 7 I report results using fixed effects.

In Table 6, international migrants are unresponsive to GDP per capita in both the origin and destination locations, indicating they are more investment-oriented. Internal migrants are less likely to return to origin in response to high GDP per capita at origin, indicating they are more consumption-oriented since only consumption-oriented migrants respond negatively to economic conditions at origin. However, internal migrants are unresponsive to GDP per capita at destination, indicating that they are more investment-oriented. These results for internal migrants may indicate that they are a group with diverse motives for migrating or they may be interpreted as inconclusive. Likewise, these results for international migrants may indicate investment-orientation or they may indicate a lack of power in estimating the response of international migrants.

Both sets of migrants are more likely to return to origin as they get older, which is what we would expect. The effect is stronger for internal migrants both in terms of the size of the effect and the level of significance.

The results for both internal and international migrants are in direct contrast to those for the OLS estimation using the cross-section data. There are several explanations for this difference. First, the year 2002 is a mass point for non-returners in the cross-section. That is, the economic conditions in 2002 dominate the comparisons between returners and non-returners in the cross-section, but the observations of non-return years is fairly evenly spread out across the years in the panel. Second, the results for the cross-section could be biased for two reasons: all of the socioeconomic data come from 2002 and thus some of the independent variables, such as wealth, may be a result of migration rather than truly independent, and omitted variables could be a problem. Lastly, it is possible that the panel lacks power since 95 percent of the observations are nonreturns.

The cross-section is comparing economic conditions in return years to the economic conditions in 2002, whereas the panel is comparing the economic conditions in all years for both returns and nonreturns. This could explain the difference between the results using the different methods if the economic conditions in 2002 are significantly different from those in the other years. T-tests for pre-2002 vs. 2002 GDP per capita suggest this may be a possibility for internal migrants since GDP per capita at both origin and destination are significantly different in these two periods. GDP per capita at origin is significantly higher (difference=2.87, p-value=0.00) for pre-2002 observations of internal migrants. Pre-2002 GDP per capita at destination is also significantly higher (difference=5.86, p-value=0.00) for internal migrants.

For international migrants, the t-tests suggest that the mass point at 2002 may explain the differences for GDP per capita at destination, but not for GDP per capita at origin. GDP per capita at destination is significantly lower (difference= -0.34, p-value=0.01) in the pre-2002 period compared to GDP per capita at destination in 2002 for international migrants. GDP per capita at origin is not statistically different (difference= -0.23, p-value=0.58) between pre-2002 and 2002 observations for international migrants. Altogether, the t-tests suggest that the mass point around 2002 explains some but not all of the differences in the results.

In addition to the mass point around 2002 causing differences between the panel and cross-section estimations, omitted variables could be biasing the cross-section results. If unobserved differences cause migrants to choose locations which are at different points in the business cycle, then this choice may bias the impact in the cross-section. And this bias may be exaggerated if the unobserved characteristic is associated with a particular migrant type. One such difference might be the level of risk aversion of each migrant. If migrants who are less risk averse look for and migrate to locations which are in a boom and if migrants who are more risk averse choose locations which experience less fluctuation in their business cycle, then this could affect the level of GDP per capita at the point of return and bias the coefficients in the cross-section. This would not be the case when using the panel data because the individual fixed effect would control for this and other unobservable characteristics.

Both bias in the coefficients and lack of power can be further investigated by running the estimation on a panel composed only of returners. Using only returners in the estimation should increase the power of the estimation since now approximately 75 percent of the observations will be nonreturns, rather than 95 percent. If the results of the restricted panel are consistent with those of the full panel then it is likely that bias in the cross-section is a problem rather than lack of power in the panel.

When the estimation is run just with the panel of returners (Table 7) our conclusions are more similar to the cross-section results. Returners from international migrations are unresponsive to GDP per capita at origin but are less likely to return when the destination economy is doing well, indicating that they are more consumption-oriented. Internal migrants are now unresponsive to GDP per capita at both origin and destination, indicating that they are more investment-oriented. With this more limited sample we cannot make conclusions about the larger migrant population, but among returners it is internal migrants who will be driving development at the origin since the results indicate that they are investment-oriented.

Again, both sets of migrants are more likely to return as they age. But, the effect is now just as strong for international migrants as it is for internal migrants both in size and significance.

Given that both the OLS estimations and the fixed effects estimations on returners lead to the same conclusions, we can have some confidence that the effects we are seeing are not attributable to omitted variables or the mass point of cross-section observations in 2002, although any conclusions about the size of the effects and whether they can be extrapolated to the larger migrant population should be approached with caution.

If we did attempt to extrapolate what the results mean we could put the changes in return probability in terms of thousands of dollars given the range of the significant coefficients from both the fixed effects estimation on returners and the OLS estimation using the return/last year of work. For example, for each thousands of dollars increase in GDP per capita at origin, the probability that an international migrant will return decreases by somewhere between 0 and 3.7 percent. International migrants facing the best GDP per capita at origin for international migrants are up to 62 percent less likely to return than those facing the worst. GDP per capita at destination has a stronger effect, decreasing the probability of return by 3 to 21.5

percent for every thousands of dollars increase. Those facing the best situation at destination are 17 to 86 percent less likely to return than those facing the worst.

On the other hand, internal migrants are up to 2.5 percent more likely to return for each thousands of dollars increase in GDP per capita at origin. Internal migrants facing the best GDP per capita at origin for internal migrants are up to 94 percent more likely to return. GDP per capita at destination has no impact on the return probability of internal migrants in any of the estimations.

Table 5 also presents results for the other independent variables used in the OLS estimation. For international migrants, those with low levels of education-primary, secondary, and high school graduates-are more likely to return than those with no schooling or with other levels of education. This is likely because those with low levels of education also make up the bulk of migrants overall and because those with high levels of education rarely return. These effects are attenuated for females with some but low levels of education. None of the interactions of good governance and education levels are statistically significant. Good governance itself has a positive and significant coefficient. Being female and being older make it more likely that a migrant to the USA will return, while having more children makes it less likely one will return, and being married has no effect. Thus, the variables most often used to control for push/pull factors of migration in previous studies of return migration, age and marital status, are not fully capturing the push/pull of return migration.

For internal migrants, those with primary to high school education are less likely to return than those with higher levels of education and those with no schooling. For internal migrants it is the interactions of being female with the education variables that are insignificant, whereas the interactions of good governance with education are significant for those with primary to high school education. A one standard deviation increase in good governance increases the likelihood of return for migrants with primary and secondary education by 8 and 12 percent, respectively. Thus, it is the internal returnees who are more highly skilled/educated rather than international migrants.

4.1 Differential responses to GDP per capita by individual characteristics

In Tables 8 and 9, I add interactions of GDP per capita with individual characteristics to the basic cross-section regression. Table 8 shows the results for GDP per capita when interacted with age and marital status. The uninteracted GDP per capita at origin term is now insignificant for international migrants but the interaction of age with GDP per capita at origin with age is significant and negative. This is consistent with a purchasing power hypothesis of return migration where, as migrants age, they become more attune to how much consumption their savings will purchase rather than how much more consumption they can earn since they are nearing the end of the working portion of their lives. In addition, older migrants are much less likely to return when GDP per capita at destination is high than are younger migrants, but all international migrants are unlikely to return when this is the case since the uninteracted GDP per capita at destination remains significant and negative for all international migrants. As discussed in Section 2, young migrants are more likely than older migrants to be investment-oriented than older migrants since they have a longer period over which to reap the rewards of their investments. Thus, the attenuated results for young international migrants indicate they are a mix of investment and consumption-oriented migrants, while older migrants are more typically consumption-oriented.

The uninteracted GDP per capita at origin term remains significant and positive for internal migrants and age does not differentiate their response to GDP per capita at the origin location. The uninteracted GDP per capita at destination term is now significant and positive for internal migrants and age attenuates their response to GDP per capita at destination. As discussed in Section 2, this is consistent with a story where older internal migrants are likely to be consumption-oriented and younger internal migrants are more likely to be investment-oriented.

Marital status is often used in studies of return migration to proxy for strong ties to the origin community. In the sample, married migrants have 2.1 children and unmarried migrants have one child on average and this difference is statistically significant (p=0.00), giving married migrants households which are larger on average by at least two (spouse + 1.1 more children). Therefore, used as a proxy for household size, I test whether married and unmarried migrants differ in their responses to GDP per capita.

The uninteracted term for GDP per capita represents the unmarried migrant's response to GDP per capita. For international migrants, unmarried migrants are responding positively and significantly to GDP per capita at origin and married international migrants respond in the same manner. Unmarried international migrants respond negatively to GDP per capita at destination and married international migrants respond even more negatively. Both of these responses indicate that international migrants overall are more likely to be consumption-oriented than investment-oriented, in particular those migrants who are married.

The response of unmarried internal migrants to GDP per capita at origin is significant and positive. Married internal migrants have a smaller response than unmarried internal migrants to origin GDP per capita and this difference may stem from a greater likelihood that married migrants are consumption-oriented or that they are more likely to be seeking human or social capital. The uninteracted term for GDP per capita at destination remains insignificant and married migrants are not responding to destination GDP per capita differentially. This insignificant response of both married and unmarried migrants is what we expect from investment-oriented migrants.

The results of interacting the dummy variables for education with GDP per capita are in Table 9, where the excluded category is migrants with no schooling. The impact of GDP per capita at origin for international migrants with no schooling is similar in levels to that at the aggregate level but it is not significant. Education does not significantly impact the response to GDP per capita at origin. GDP per capita at destination indicates that international migrants with no schooling are less likely to return when the destination economy is on an upswing. The response of those with higher levels of education is not significantly different from those with no schooling. International migrants with some education but holding a high school diploma or less are even more likely to stay at destination. This shows that migrants to the USA, regardless of education level are consumption-oriented, with the strongest consumption motivations lying with those with some education. This result is not necessarily inconsistent with Reinhold and Thom (2009) since their study includes only return migrants with post-migration Mexico work experience, which is a sub-sample of the return migrants in the sample used here. As discussed in Section 2, showing that international migrants are predominantly consumption-oriented does not preclude the possibility of some investment-oriented migrants nor the possibility that consumption-oriented migrants can engage in skill upgrading while pursuing their consumption goals.

As with international migrants, education is not differentiating migrant responses to GDP per capita at origin for internal migrants. Those with no schooling are responding to GDP per capita at origin similarly to those with other levels of education and this response is not significant. This is also true of the response of those with no schooling to GDP per capita at destination. However, those with a primary or secondary education and college graduates have a positive response to GDP per capita at destination. All of these responses are consistent with internal migrants being investment-oriented, and in particular for those with higher education levels.

5 Alternate measures of GDP per capita

5.1 Is current GDP per capita the correct measure to use?

One may think that it is not current GDP per capita but GDP per capita in the recent past that is driving return. To test this possibility, I add two years of lagged GDP per capita data to the basic estimating equation. Because pre- and post-1993 GDP per capita are not comparable in Mexico, observations for 1993 and 1994 were dropped along with migrants from Mexican states which are missing data during the time period. The results of this estimation are in Table 10. The impact of GDP per capita at origin for internal migrants is now insignificant. GDP per capita at destination continues to have an insignificant impact on an internal migrant's return decision. Together, these impacts still point to internal migrants being investment-oriented. The sign and significance of both coefficients for international migrants remain the same. The magnitude of the coefficients for international migrants changes by less than ten percent. Thus, re-estimating the basic equation with this limited sample shows that we would draw the same conclusions as we did with the full sample.

Both current and prior year's GDP per capita at origin have a positive impact on an internal migrant's probability of returning. GDP per capita at origin from two years prior to return has a negative impact on return. Its size is one-third that of the current year's impact and thus the current year decision of an internal migrant facing the third year of a boom in the origin location is still more likely to return than to not. Both current and prior year's GDP per capita at destination are insignificant. GDP per capita at destination from two years prior has a small negative impact on return, indicating that internal migrants are not exclusively investment-oriented.

In contrast, all of the measures for GDP per capita at origin have an insignificant effect on migrants to the USA. It seems that the aggregate negative effect is more related to the impact of GDP per capita in the recent past than in the current year. Current year GDP per capita at destination is significant and now positive for migrants to the USA, indicating that they too are likely to be investment-oriented migrants. Prior year GDP per capita at destination is insignificant. GDP per capita at destination from two year's prior is negative and significant. It is larger in size than the impact of current year GDP per capita and thus the current year decision of a migrant to the USA facing a boom at destination is still less likely to return, but the large sizes of the coefficients lead us to think there may be problems of correlations.

Overall, I do not observe any indication that the use of contemporaneous shocks is biasing strongly the results, but GDP per capita in the recent past may be highly relevant for the migrant's return decision.

5.2 Other measures used in the literature on cyclical inflows

In Table 11 I test how different measures of income affect the estimation results. I first investigate the impact of the difference in GDP per capita between the origin and destination. Given that both internal and international migrants and returners and non-returners face different differentials in GDP per capita between locations, I test whether the difference is important in determining return. The expectation is that the difference is important for consumption-oriented migrants since they are assessing the marginal benefit versus the marginal cost of migration, whereas the difference is less important for investment-oriented migrants who are concerned with gaining a certain level of capital (financial or otherwise) in order to make their investment, except as this difference determines how quickly they meet their needs for capital. The results in column 2 support the previous finding that migrants to the USA are more likely to be consumption-oriented since as the difference between origin and destination grows they are less likely to return and this effect is highly significant. Moreover, the impact on internal migrants is insignificant supporting the finding that internal migrants are more likely investment-oriented.

The results in the rest of the table test whether other measures used in the literature would change our general conclusions. These measures mainly add the unemployment rate to the basic equation either by simple addition or multiplicatively. In column 3, I add the unemployment rate to the basic cross-section equation as in Table 2 of Mayda (2010). Doing so does little to change the basic results on GDP per capita. Migrants to the USA are responding positively to the unemployment rate at origin and negatively to the unemployment rate at destination. Both are significant and in the opposite direction that we would expect. Internal migrants, on the other hand, are responding to the unemployment rate as expected and only the impact of the unemployment rate at destination is significant, which may point to the fact that these migrants are returning to make an investment so that uncertainty of employment is unlikely to affect their willingness to return.

In columns 4, 5, and 6, I use measures from Ortega and Peri (2009). Unemployment here is added multiplicatively to the equation, multiplying GDP per capita and the employment rate. Doing so has little effect on the impact and significance of GDP per capita in column 4 and again in column 5 where the logarithm of the Employment Rate*GDP per capita is taken. Decomposing the logarithm in column 6, does change the basic results and strengthens the argument that internal migrants are more investment-oriented than migrants to the USA. The impact and significance of GDP per capita for internal migrants changes little for both origin and destination. GDP per capita at origin becomes insignificant for migrants to the USA and GDP per capita at destination remains negative and significant, although only slightly so. Instead the employment rate is highly significant at both origin and destination, but with the same puzzling signs which are opposite from those expected.

In summary, these exercises suggest that using alternative measures of cyclicality would not change our general conclusions, although it appears that international migrants may respond counter-intuitively to unemployment conditions, conditional on GDP measures.

6 Conclusion

In this paper I show that internal return migrants in Mexico are more investment-oriented than international migrants who return from the USA. Internal returners are more likely to return when the origin economy is doing well, but not international returners. Internal returners are unresponsive to the destination economy while international returners are less likely to return when the destination economy is doing well. Taken as a whole, the cyclical nature of return migration highlights the fact that the migrants who are most likely to invest after return are migrating to other Mexico locations.

Remittances from international migration are large, but the results in this paper indicate that they are channeled mainly to consumption rather than investment. While these findings are likely unique to Mexico and may be unique for returners, they highlight the need for politicians to not go blindly into policies which promote one form of development over another, but the need for a careful understanding of the motivations of migrants, how to direct returnees towards investing in the origin community/country, and how to provide the right environment to make an impact. These results should be further investigated by looking at the activities that migrants engage in after returning from both internal and international migrations, something that Mexico may want to do if it wants to harness migrants in the development process.

Table 1. Variable Definitions and Means

Variable	Description	Mean	Std. Dev.
Return	0/1 indicating if migrant is working in the origin location in the last recorded year of work	0.32	0.46
Female	1 indicates female gender	0.55	0.50
Age	age of migrant in the last recorded year of work for those who have not returned or in the return year for those who have returned	35.32	15.30
Number of children	number of children in household in 2002	1.65	2.69
Married	0/1 indicating migrant is married in 2002	0.57	0.50
Distance travelled (kilometers)	kilometers between origin location and migration destination	109.93	84.73
Border States	0/1 indicating a Mexican state which lies on the border with the USA	0.21	0.41
No schooling	0/1 indicating migrant reported not ever having attended school or having attended only preschool	0.12	0.32
Primary education	0/1 indicating migrant reported having attended only primary school	0.58	0.49
Secondary education	0/1 indicating migrant reported having attended secondary school, but did not graduate	0.20	0.10
High school Graduate	0/1 indicating migrant reported graduating from secondary school	0.05	0.22
Technical Degree	0/1 indicating migrant holds a technical degree or commercial license	0.02	0.15
College Graduate	0/1 indicating migrant is a college graduate	0.02	0.15
GDP per capita at origin[1]	GDP per capita in migrant's origin state, in thousands of dollars	6.71	5.12
GDP per capita at destination[1]	GDP per capita in migrant's destination state, USA for international and Mexico for internal, in thousands of dollars	11.92	10.75
Seasonal	0/1 indicating migrant had periodic episodes of work in both origin and destination locations	0.30	0.16
Wealth	0-10 index ranking of household wealth calculated as in Filmer and Pritchett (2001)	4.97	1.82
Good Governance	0-25 index ranking of origin state's level of corruption and good governance practices from Transperencia Mexicana	9.60	5.60

Source: ENHRUM data and author's calculations from ENHRUM data unless otherwise noted in the definition

[1]Mean and Std. Dev. Are for the return/last year of work

Table 2. Characteristics of Nonseasonal Migrants by Destination				
Variables	Migrants to USA	Migrants within Mexico	Difference	P-value
Female	0.62	0.53	0.09	0.02
	(0.49)	(0.50)		
Age	35.63	35.04	0.59	0.59
	(15.37)	(14.89)		
Number of children	1.75	1.54	0.21	0.24
	(2.65)	(2.48)		
Married	0.58	0.57	0.01	0.77
	(0.49)	(0.50)		
Distance travelled	110.39	112.79	-2.4	0.7
	(89.30)	(82.47)		
Border States	0.35	0.12	0.23	0
	(0.48)	(0.32)		
No schooling	0.12	0.13	-0.01	0.84
	(0.33)	(0.33)		
Primary education	0.58	0.57	0.01	0.9
	(0.49)	(0.50)		
Secondary education	0.20	0.20	0	0.81
	(0.40)	(0.40)		
High school Graduate	0.04	0.06	-0.02	0.31
	(0.20)	(0.23)		
Technical Degree	0.03	0.02	0.01	0.93
	(0.16)	(0.15)		
College Graduate	0.04	0.02	0.02	0.098
	(0.19)	(0.14)		
GDP per capita at origin in return year or last year of work	6.04	7.87	-1.83	0
	(3.64)	(6.21)		
GDP per capita at origin at person-year level[1]	6.66	8.71	-2.05	0
	(4.53)	(8.03)		
GDP per capita at destination in return year or last year of work	10.22	14.60	-4.38	0
	(0.91)	(15.31)		
GDP per capita at destination at person-year level[1]	9.57	16.56	-6.99	0
	(1.37)	(19.65)		
Wealth	5.88	4.38	1.5	0
	(1.59)	(1.74)		

Good Governance	7.75		11.67		-3.92		0
	(4.38)		(6.29)				
Number of observations[1]	358		415				
Variable Definitions can be found in Table 1, Standard Deviations in Parentheses							
Value defines either the proportion of migrants who possess characteristic or the mean value over all migrants of that type							
[1]Number of observations at person-year level are 2185 for migrants to the USA and 2472 for migrants within Mexico.							

Table 3. Characteristics of Returners and Non-returners by Destination

	Migrants to USA				Migrants within Mexico			
Variables	Non-returners	Returners	Difference	P-value	Non-returners	Returners	Difference	P-value
Female	0.62	0.57	0.05	0.44	0.49	0.63	-0.14	0.01
	(0.49)	(0.50)			(0.50)	(0.49)		
Age	35.20	37.67	-2.47	0.25	35.66	33.40	2.26	0.17
	(15.05)	(16.75)			(15.50)	(13.07)		
Number of children	1.76	1.75	0.01	0.98	1.46	1.74	-0.28	0.3
	(2.63)	(2.78)			(2.44)	(2.57)		
Married	0.59	0.54	0.05	0.44	0.57	0.58	-0.01	0.97
	(0.49)	(0.50)			(0.50)	(0.50)		
Distance travelled	113.02	98.07	14.95	0.23	118.53	97.44	21.09	0.02
	(89.84)	(86.35)			(78.98)	(89.74)		
Border States	0.35	0.33	0.02	0.81	0.11	0.14	-0.03	0.36
	(0.48)	(0.48)			(0.31)	(0.35)		
No schooling	0.11	0.18	-0.07	0.17	0.15	0.08	0.07	0.07
	(0.32)	(0.38)			(0.35)	(0.27)		
Primary education	0.56	0.65	-0.09	0.18	0.54	0.65	-0.11	0.06
	(0.50)	(0.48)			(0.50)	(0.48)		
Secondary education	0.21	0.14	0.07	0.25	0.22	0.16	0.06	0.18
	(0.41)	(0.35)			(0.41)	(0.37)		
High school Graduate	0.04	0.03	0.01	0.66	0.06	0.05	0.01	0.8
	(0.21)	(0.18)			(0.24)	(0.23)		
Technical Degree	0.03	0#	0.03	0.16	0.02	0.03	-0.01	0.84
	(0.17)	(0.00)			(0.15)	(0.16)		
College Graduate	0.05	0#	0.05	0.08	0.01	0.04	-0.03	0.14
	(0.20)	(0.00)			(0.11)	(0.19)		
GDP per capita at origin	6.21	5.23	0.98	0.05	7.25	9.52	-2.27	0.001
in return year or last year	(3.55)	(4.01)			(5.64)	(7.33)		

Table 3. Characteristics of Returners and Non-returners by Destination (Continued)

	Migrants to USA				Migrants within Mexico			
Variables	Non-returners	Returners	Difference	P-value	Non-returners	Returners	Difference	P-value
GDP per capita at origin at person-year level[1]	6.72	5.08	1.64	0.002	8.69	9.06	-0.37	0.63
	(4.55)	(3.76)			(8.07)	(7.27)		
GDP per capita at destination in return year or last year of work	10.53	8.86	1.67	0	13.53	17.46	-3.93	0.02
	(0.37)	(1.23)			(13.80)	(18.52)		
GDP per capita at destination at person-year level[1]	9.57	9.55	0.02	0.92	16.55	16.95	-0.41	0.83
	(1.37)	(1.24)			(19.72)	(18.21)		
Wealth	5.9	5.76	0.14	0.53	4.32	4.53	-0.21	0.28
	(1.56)	(1.76)			(1.74)	(1.74)		
Good Governance	7.78	7.63	0.15	0.8	11.36	12.55	-1.19	0.08
	(4.47)	(3.66)			(6.12)	(6.65)		
Number of observations[1]	295	63			302	113		

Variable Definitions can be found in Table 1, Standard Deviations in Parentheses

Value defines either the proportion of migrants who possess characteristic or the mean value over all migrants of that type

[1]Observations at person-year level are for migrants to the USA, non-returners 2112, returners 73, for migrants within Mexico, non-returners 2356, returners 116.

Table 4. Differences in Characteristics of Returners and Non-returners by Destination					
	USA and Mexico Returners			USA and Mexico Non-returners	
Variables	Difference	P-value		Difference	P-value
Female	-0.06	0.46		0.13	0.001
Age	4.27	0.06		-0.46	0.71
Number of children	0.01	0.99		0.3	0.16
Married	-0.04	0.65		0.02	0.61
Distance travelled	0.63	0.96		-5.51	0.43
Border States	0.19	0.003		0.24	0
No schooling	0.1	0.06		-0.04	0.23
Primary education	0	0.95		0.02	0.69
Secondary education	-0.02	0.77		-0.01	0.73
High school Graduate	-0.02	0.52		-0.02	0.39
Technical Degree	-0.03	0.19		0.01	0.58
College Graduate	-0.04	0.13		0.04	0.01
GDP per capita at origin in return year or last year of work	-4.29	0		-1.04	0.007
GDP per capita at origin at person-year level[1]	-3.97	0		-1.97	0
GDP per capita at destination in return year or last year of work	-8.6	0.0003		-3	0.0002
GDP per capita at destination at person-year level[1]	-7.4	0.0007		-6.98	0
Wealth	1.23	0		1.58	0
Good Governance	-4.92	0		-3.58	0

Variable Definitions can be found in Table 1

Levels of characteristics of each type of migrant can be found in Table 3

[1]Observations at person-year level are for migrants to the USA, non-returners 2112, returners 73, for migrants within Mexico, non-returners 2356, returners 116.

Table 5. Results on Return Migration by Destination for Nonseasonal Migrants using GDP per capita (Cross-Section)

	Destination		
Variables	USA	Mexico	Difference
GDP per capita at origin	-0.037***	0.025***	-0.062***
	(0.010)	(0.006)	(0.012)
GDP per capita at destination	-0.215***	0.001	-0.206***
	(0.018)	(0.001)	(0.018)
Female	0.372***	-0.053	0.425**
	(0.121)	(0.124)	(0.176)
Age	0.024***	-0.019***	0.043***
	(0.007)	(0.007)	(0.009)
Age Squared	-0.0002**	0.0002**	-0.0004***
	(0.00008)	(0.00008)	(0.0001)
Number of Children	-0.023**	0.011	-0.034**
	(0.011)	(0.012)	(0.016)
Married	-0.010	0.002	0.008
	(0.043)	(0.044)	(0.062)
Distance travelled	0.0002	-0.0008***	0.0008**
	(0.0002)	(0.0002)	(0.0004)
Border State	0.085	-0.009	0.093
	(0.058)	(0.075)	(0.095)
Wealth	.015	0.006	0.009
	(0.015)	(0.012)	(0.019)
Good Governance	0.051***	-0.049***	0.099***
	(0.015)	(0.010)	(0.018)
Primary education	0.485***	-0.402***	0.887***
	(0.161)	(0.143)	(0.202)
Secondary education	0.540***	-0.680***	1.220***
	(0.185)	(0.159)	(0.231)
High school Graduate	0.725***	-0.463**	1.188***
	(0.240)	(0.211)	(0.309)
Technical Degree	1.164	1.164	0
	(1.130)	(1.130)	(0)
College Graduate	0.899	0.555	0.345
	(0.823)	(0.395)	(0.909)
Female Migrant*Primary Education	-0.282**	0.178	-0.460**
	(0.134)	(0.122)	(0.178)
Female Migrant*Secondary Education	-0.411***	0.047	-0.459**
	(0.153)	(0.143)	(0.206)
Female Migrant*High School Graduate	-0.485*	-0.021	-0.465
	(0.251)	(0.202)	(0.320)
Female Migrant*Technical Degree	-0.336	-1.394	1.058

	(0.340)		(1.168)		(1.233)
Female Migrant*College Graduate	-0.295		-0.358		0.062
	(0.242)		(0.346)		(0.422)
Primary education*Good Governance	-0.020		0.029***		-0.050***
	(0.014)		(0.010)		(0.017)
Secondary education*Good Governance	-0.021		0.045***		-0.066***
	(0.017)		(0.011)		(0.020)
High School Graduate*Good Governance	-0.026		0.033**		-0.059**
	(0.021)		(0.015)		(0.025)
Technical Degree*Good Governance	-0.128		0.019		-0.146
	(0.181)		(0.027)		(0.183)
College Graduate*Good Governance	-0.092		-0.019		-0.072
	(0.125)		(0.030)		(0.128)
Number of Observations	358		415		
R-squared	0.243				
Variable Definitions can be found in Table 1					
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1					

Table 6. Results on Return Migration by Destination for Nonseasonal Migrants (Panel of All Migrants)

	Destination		
Variables	USA	Mexico	Difference
GDP per capita at origin	-0.0001	-0.003*	0.002
	(0.002)	(0.013)	(0.023)
GDP per capita at destination	-0.002	-0.0006	-0.001
	(0.002)	(0.005)	(0.023)
Age	0.007*	0.019***	0.012**
	(0.004)	(0.004)	(0.005)
Age-squared	0.0001	-0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)
Number of Observations	2185	2472	
R-squared	0.039		

Variable Definitions can be found in Table 1

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7. Results on Return Migration by Destination for Nonseasonal Migrants (Panel of Returners)

	Destination		
Variables	USA	Mexico	Difference
GDP per capita at origin	0.006	0.0002	0.006
	(0.014)	(0.007)	(0.015)
GDP per capita at destination	-0.030**	-0.003	-0.027**
	(0.013)	(0.003)	(0.013)
Age	0.108***	0.074***	0.033
	(0.032)	(0.023)	(0.040)
Age-squared	0.0003	0.0006	-0.0003
	(0.0004)	(0.0004)	(0.0006)
Number of Observations	73	116	
R-squared	0.292		

Variable Definitions can be found in Table 1

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8. Results with Interactions of Age and Marital Status with GDP per capita

	Age		Martial Status	
Variables	USA	Mexico	USA	Mexico
Characteristic	0.076***	-0.002	0.003	0.049
	(0.009)	(0.007)	(0.011)	(0.071)
Characteristic squared	0.000	0.000	-	-
	(0.000)	(0.000)	-	-
GDP per capita at origin	0.001	0.028***	0.015**	0.034***
	(0.0175)	(0.010)	(0.006)	(0.009)
GDP per capita at destination	-0.074***	0.007**	-0.139***	-0.0003
	(0.027)	(0.003)	(0.021)	(0.002)
Characteristic*GDP per capita at origin	-0.001**	-0.0002	0.003	-0.014*
	(0.0004)	(0.0003)	(0.011)	(0.007)
Characteristic*GDP per capita at destination	-0.006***	-0.0001*	-0.243***	0.003
	(.0008)	(0.0001)[i]	(0.039)	(0.003)
Number of Observations	358	415	358	415
R-squared	0.315		0.286	
Likelihood Ratio Test:				
Null: No interactions with characteristics	75.86***		44.33***	

Variable Definitions can be found in Table 1, Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

All estimations include controls at individual and state level as in Table 4.

[i]Actual value is 0.00007

Table 9. Results with Interactions of Education Variables and GDP per capita

	Uninteracted terms		Interaction with GDP per capita at origin		Interaction with GDP per capita at destination	
Variables	USA	Mexico	USA	Mexico	USA	Mexico
GDP per capita at origin	-0.034	0.003	-	-	-	-
	(0.024)	(0.021)	-	-	-	-
GDP per capita at destination	-0.099***	-0.006	-	-	-	-
	(0.026)	(0.004)	-	-	-	-
Primary Education	2.483***	-0.272*	0.002	0.019	-0.234***	0.008*
	(0.366)	(0.156)	(0.026)	(0.021)	(0.038)	(0.004)
Secondary Education	1.424***	-0.558***	-0.021	0.004	-0.123**	0.011**
	(0.543)	(0.172)	(0.030)	(0.027)	(0.054)	(0.005)
High School Diploma	3.820**	-0.164	-0.013	0.059	-0.344*	0.0036
	(1.821)	(0.242)	(0.055)	(0.050)	(0.178)	(0.007)
Technical Certificate	0.341[i]	0.341[i]	0.030	0.058	-0.014	-0.005
	(0.551)	(0.551)	(0.126)	(0.068)	(0.072)	(0.013)
College Graduate	1.297[i]	1.297[i]	0.027	0.096	-0.111	0.019**
	(1.047)	(1.047)	(0.071)	(0.152)	(0.147)	(0.009)
Number of Observations	358	415				
R-squared	0.303					
Likelihood Ratio Test						
Null: No interactions with characteristics	62.85***					

Variable Definitions can be found in Table 1, Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

All estimations include controls at individual and state level as in Table 4.

Table 10. Results with Lagged GDP variables				
	Basic		Destination	
Variables	USA	Mexico	USA	Mexico
Current GDP per capita at origin	-0.040***	-0.011	0.084	0.175***
	(0.010)	(0.015)	(0.055)	(0.040)
Current GDP per capita at destination	-0.198***	-0.001	1.64***	0.023
	(0.021)	(0.002)	(0.147)	(0.020)
GDP per capita at origin-prior year			-0.052	0.313***
			(0.113)	(0.085)
GDP per capita at destination-prior year			0.044	0.003
			(0.037)	(0.004)
GDP per capita at origin-two years prior			-0.005	-0.053***
			(0.012)	(0.008)
GDP per capita at destination-two years prior			-1.809***	-0.007*
			(0.149)	(0.004)
Number of Observations	348	292	348	292
R-squared	0.249		0.587	
Variable Definitions can be found in Table 1, Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				
All estimations include controls at individual and state level as in Table 4.				
The sample size is reduced because pre-1993 GDP per capita is not comparable to post-1993 GDP per capita in Mexico and observations from 1993 and 1994 were dropped.				

Table 11. Results using Alternative Measures of GDP per capita

	[1] Basic		[2] Difference		[3] Mayda (2010)	
Variables	USA	Mexico	USA	Mexico	USA	Mexico
GDP per capita at origin	-0.037***	0.025***			-0.021*	0.025***
	(0.010)	(0.006)			(0.011)	(0.006)
GDP per capita at destination	-0.215***	0.001			-0.148***	-0.001
	(0.018)	(0.001)			(0.023)	(0.002)
Difference in GDP per capita			-0.024***	0.002		
			(0.009)	(.002)		
Unemployment Rate at origin					0.051**	-0.006
					(0.023)	(0.032)
Unemployment Rate at destination					-0.102***	0.071***
					(0.038)	(0.025)
Number of Observations	358	415	358	415	344	415
R-squared	0.243		0.105		0.253	
	[4] Employment Rate*GDP per capita		[5] Logarithms		[6] Decomposition	
Variables	USA	Mexico	USA	Mexico	USA	Mexico
GDP per capita at origin	-0.035***	0.025***	-0.126***	0.144***	-0.015	0.146***
	(0.011)	(0.007)	(0.042)	(0.047)	(0.047)	(0.046)
GDP per capita at destination	-0.193***	0.001	-0.602***	0.027	-0.229*	0.003
	(0.021)	(0.002)	(0.115)	(0.021)	(0.137)	(0.023)
Employment Rate at origin					-7.48***	-1.142
					(2.29)	(3.222)
Employment Rate at destination					17.70***	-6.271***
					(4.02)	(2.406)
Number of Observations	344	415	344	415	344	415
R-squared	0.217		0.163		0.210	

Variable Definitions can be found in Table 1, Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
All estimations include controls at individual and state level as in Table 4.
The number of observations is reduced because unemployment data is lacking for some Mexican states in some of the earlier years.

Chapter 3: Health Service Use Among the Previously Uninsured: Is Subsidized Health Insurance Enough?[2]

1 Introduction

More than 40 million individuals lack health insurance in the United States (Cohen and Martinez, 2009). The lack of health insurance coverage mostly occurs among those younger than 65years because the United States finances basic health insurance coverage for nearly all citizens 65 years and older through the Medicare program. Uninsured individuals before age 65 years differ from the insured on several observed dimensions. For example, the uninsured have less education and lower income than the insured (Cohen and Martinez, 2009). The uninsured may also differ from the insured in ways more difficult to observe and measure, including possible differences in the degree of risk aversion, propensity to use medical care, proximity to different types of healthcare providers, and health endowment. Because of these unobserved differences, it is difficult to attribute all differences in the use of health services between the uninsured and the insured to the difference in insurance status rather than to these other differences in characteristics.

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[2] This work is joint with Sandra L. Decker, Jalpa A. Doshi, and Daniel Polsky and was published in *Health Economics* (2012) under the same title.

The insurance status of most individuals in the United States changes at age 65 years. Most individuals who are privately insured before age 65 years transition to Medicare at age 65 years. The effect of this change in health insurance status for individuals who were privately insured before age 65 years may depend on the generosity of Medicare relative to their insurance plans before age 65 years and on whether these individuals have or obtain insurance supplemental to Medicare beginning at age 65 years. The effect of the change in health insurance status at age 65 years for those uninsured before age 65 years is less ambiguous because these individuals will experience a substantial decline in the out-of-pocket cost of health care at the point of service at age 65 years. Although past research indeed suggests that the previously uninsured increase their use of health services upon becoming insured at age 65 years, this increase does not mean that they then use health services after age 65 years to the same extent and in the same way compared with individuals who were previously insured.

Difficulty in changing habits or differences in the characteristics of previously uninsured compared with insured individuals may result in the continued different use of the healthcare system. The relationship between the health insurance status and the subsequent pattern of service use under Medicare is important for several reasons. First, as healthcare reform legislation seeks to increase health insurance coverage rates through subsidies for coverage, we may gain insights into how the uninsured might access health care upon obtaining subsidized coverage from how the previously uninsured near elderly use health services when they enter Medicare at age 65 years.

We do not know if subsidized coverage is enough for the previously uninsured to benefit from coverage in the way that is typical of an insured beneficiary. Second, policy makers have sometimes suggested that the cost of insuring the uninsured earlier in life may be partly offset by reduced Medicare expenditures for these individuals once they reach age 65 years (Baucus, 2009), a possibility that may be informed by examining current Medicare expenditures for the previously uninsured relative to the insured.

This article uses Medicare claims data linked to two different surveys to investigate the relationship between health insurance status before entering Medicare and medical service use once on Medicare. In addition to analyzing Medicare expenditures, we also use Medicare claims to count the number of hospitalizations and physician visits, which allows for a more detailed investigation of the associations between health service use under Medicare and insurance status before age 65 years.

2 Background

The economic models of the demand for medical care suggest that the use of medical care depends on the price of medical care and one's tastes for or value put on medical care, often substituted by variables such as health status, income, education, age, race, and gender (Grossman, 1972). The components of the price of health care include, among others, out-of-pocket costs at the point of service, time costs, and transportation costs. Relative to having no insurance, Medicare eligibility decreases the out-of-pocket price of health care and is expected to increase the use of health services. Indeed, previous research has found that the original introduction of Medicare in the 1960s increased the use of hospital care among the elderly, although the magnitude of the increase is unclear, with some evidence suggesting quite large effects (Finkelstein, 2007) and others considerably smaller (Chay et al., 2010).

Currently, Medicare eligibility at age 65 years results in an abrupt decline in the probability of being uninsured in the United States. Because this decline in the probability of being uninsured results in a decline in the out-of-pocket price of medical care for previously uninsured individuals, it would be expected that these individuals would increase their use of medical care, although the magnitude of the increase and whether this results in higher expenditures for those who were uninsured before age 65 years relative to those who were insured is not certain. The RAND health insurance study of the 1970s (Newhouse, 1993) randomly assigned 5809 nonelderly enrollees from six sites to insurance plans with different rates of coinsurance. Results demonstrated that although medical care use did respond to price, the rate of response was fairly small compared with many other goods and services. The response to price also varied by the type of medical care, with the demand for hospital care being least price responsive and the demand for "well care" most price responsive. If insurance status before age 65 years were randomly assigned, then one would expect the previously uninsured to increase their use of healthcare services at age 65 years, but less for hospital care and other types of services for which the demand is relatively inelastic than for outpatient services.

Because the demand for "big ticket" items like hospital care is in general less elastic compared with the other types of care, one may not expect spending to increase dramatically for the previously uninsured at age 65 years. In addition, insurance status before age 65 years is, of course, not randomly assigned.

The response at age 65 years could be less than or greater than that predicted if the insurance status was randomly assigned. To the extent that the uninsured have "less taste for medical care" compared with the insured, are less risk averse than average, or have less geographic access to care, their response to a reduction in the out-of-pocket price of health care may be less than that of the population average. The response of the near elderly to the gain in health insurance at age 65 years has been the subject of some recent research. The first study (Lichtenberg, 2002) found that the use of health services increases discontinuously at age 65 years for the population as a whole in the United States. Using panel data from the Health and Retirement Study (HRS), McWilliams et al. (2003 and 2007) found a larger increase in the self-reported use of some healthcare services for those who had been uninsured before the age of 65 years than for others. Because health insurance status is not exogenous, Decker (2005) and Card et al., (2008) examined changes in the use of healthcare services before and after age 65 years by education status and reported larger increases in the use of health services among those with less than a high school education, who are more likely to be uninsured, compared with others.

One previous study (McWilliams et al. 2009) used the HRS linked to Medicare data and found that those who were uninsured had statistically significantly higher Medicare expenditures after age 65 years compared with those who were insured before age 65 years. In the article of McWilliams et al. (2009), the results were interpreted as potential savings from subsidized insurance for the uninsured. To interpret the results as the effect of health insurance status on health and future medical expenditures, the measured correlation cannot be attributed to omitted factors nor can it be attributed to a reverse relationship (i.e. health status determining coverage). Because declines in health may lead to changes in employment and health insurance status, there is a strong possibility of a reverse relationship between health and health insurance status (either becoming uninsured or becoming eligible for public insurance) before age 65 years, especially among middle-aged adults. This may be true for several reasons. Individuals in poor health may not be able to work. Any resulting voluntary or involuntary job loss associated with poor health may also result in the loss of employer-provided health insurance. Individuals who qualify for Medicare before age 65 years due to participation in the Social Security Disability Insurance (SSDI) qualify only after a 24-month waiting period after the SSDI entitlement. Because they must be too disabled to work to qualify for SSDI, a substantial fraction is uninsured during the waiting period (Riley, 2006). For these individuals, the onset of disability precedes the period of the lack of insurance as well as the transition to public insurance. Finally, some individuals may become eligible for Medicaid before age 65 through state medically needy programs, which allow individuals to “spend down” to Medicaid eligibility by incurring medical and/or remedial care expenses to offset income and reduce it a level below the maximum allowed for Medicaid eligibility. These disabled or medically needy individuals are likely to have persistently high medical expenditures, which could not have been avoided by insuring them, because the lack of insurance or transition to public insurance resulted from the onset of disability rather than resulting in it. The inclusion of those who transition into public health insurance before turning 65 years old in the comparison of previously insured and previously uninsured may be particularly likely to lead to biased results.

Our goal was to describe the use of health services for the previously uninsured and previously insured, controlling for observable differences between them and excluding those who qualify for public health insurance before age 65years. We do not assume that we will be able to control for all omitted factors. Our secondary goal was to caution against a literal causal interpretation of our findings and reconcile our results with the McWilliams et al. (2009) study by showing the sensitivity of our results to observable factors and the inclusion of individuals who were publicly insured before age 65 years.

3 Data and Methods

3.1 National Health Interview Survey–Medicare data

The analysis using the National Health Interview Survey (NHIS)–Medicare relies on data from the NHIS, conducted by the National Center for Health Statistics (NCHS), matched to Medicare enrollment and claims data collected from the Centers for Medicare and Medicaid Services. The NHIS is a continuous cross-sectional survey that provides information on the health status and demographic attributes of individuals in a large sample of households. The NHIS follows a multistage probability design using geographically defined sampling units to select a nationally representative sample of households for interview. Medicare data for 1991–2007 are available for respondents to the 1994–2005 NHIS who agreed to provide personal identification information to NCHS and for whom validated matches to Medicare administrative records were found.

Our initial sample consisted of 11,367 individuals who were age 63 or 64 years at the time of the NHIS survey but who turned 65 years old before January 1, 2007, and therefore have the potential to have at least 1year of Medicare claims after turning 65 years old. Of the 9588 records remaining after we dropped individuals missing information on survey variables used in the analysis, 6272 (65%) match to Medicare records. The primary reason that individuals in the NHIS do not match to Medicare records is that these respondents declined to supply their social security number for matching (National Center for Health Statistics (NCHS), 2011). Of the remaining 6139 individuals who are alive and eligible for Medicare Part A for at least 1year after turning 65 years old, we excluded 719 who were not in fee-for-service Medicare for at least a year before entering an HMO and 781 individuals who do not have Part B coverage for an entire year after turning 65 years old. The final sample has 5090 individuals with 500 identified as uninsured, 716 publicly insured, and 2892 privately insured. Sampled individuals are followed for, on average, 6.6 years after turning 65 years old.

Insurance status is based on a point-in-time measure at age 63 or 64 years. For 93% of the uninsured in the NHIS sample who responded to a question about length of time since coverage, 74% had been uninsured for at least 3 years.

3.2 HRS–Medicare data

The original age-eligible cohort of the HRS began in 1992 as a national longitudinal study of the noninstitutionalized population born between 1931 and 1941 (i.e. persons age 51–61 years at the time of the baseline survey) and their spouses. Respondents and their spouses have been reinterviewed every 2 years since. Medicare data for the years 1993 through 2005 have been linked to the HRS for respondents who gave consent to do so by providing their Medicare numbers.

Our study sample included primary respondents and spouses who turned 65 by December 31, 2004, in order for the entire sample to potentially have at least 1 year of Medicare claims after turning 65 years old. From these 9227 individuals, 5968 (64%) matched to Medicare records. After applying the same additional exclusion criteria as were used for NHIS, the final HRS sample has 4108 individuals with 500 identified as uninsured, 716 as publicly insured, and 2892 as privately insured. Sampled individuals are followed for, on average, 4.8 years after turning 65 years old.

As with the NHIS, the uninsured are defined as those who indicated that they had no form of private or public insurance at the time of the survey. In the case of the HRS, this was measured at the survey wave before turning 65 years old (or the latest wave observed for the small fraction of the sample responding in some waves before age 65 years but not the wave right before age 65 years). After age 65 years, respondents were classified as having supplemental insurance if in the first wave after turning 65 years old, in addition to Medicare coverage, they reported having insurance through an employer or former employer, as an individual through a Medigap plan, or through government sources such as Medicaid or the Veterans Administration.

The HRS sample weights account for attrition (in addition to the complex sample design) through a poststratification of the HRS to the Current Population Survey by age, sex, race, ethnicity, and marital status groups. This stratification accounts for differential nonresponse over time by those major demographic groups. Because differential attrition by insurance status remained (i.e. persons who were uninsured are more likely to be lost to follow-up than persons who were insured), we used the Current Population Survey to apply an additional adjustment to the HRS weights to match insurance status totals (Polsky et al., 2009). The adjusted weights are used in all analyses.

3.3 Outcomes

The primary study outcomes of annual Medicare expenditures and service use were calculated using Medicare claims data linked to the surveys by summing expenditure and service events for each individual at each age beginning at age 65. Medicare expenditures are calculated from the claims files and include Medicare payments for Medicare-covered services plus any beneficiary deductible and coinsurance payments paid by the beneficiary (or supplemental insurance). They also include the primary payer payment amount if the primary payer is different than Medicare. Expenditures are expressed in $2000 using the medical care component of the consumer price index (U.S. Bureau of Labor Statistics, 2011).

Additional outcome measures include the number of inpatient stays and physician visits at physician offices, hospital outpatient departments, and emergency rooms. For visits to office-based providers, we also classified visits according to specialty or the type of provider seen: (i) physicians in general practice (specialties of general practice, family practice, internal medicine, or geriatrics), (ii) physicians in specialties, and (iii) physicians of unknown specialty or nonphysician providers (e.g. physical or occupational therapists, audiologists, certified nurse anesthetists).

3.3 Analysis

We first summarized mean differences in medical expenditures for the previously uninsured and publicly insured compared with the privately insured. Because medical expenditures have several properties indicating that the analysis of expenditures by ordinary least squares would be biased and inefficient (Jones, 2000), we analyzed expenditures using generalized linear models with a gamma distribution and log link function (McCullagh and Nelder, 1989; Manning and Mullahy, 2001; Buntin and Zaslavsky, 2004). The number of hospital and physician visits was analyzed using a negative binomial distribution. We presented adjusted differences in expenditures between the previously uninsured and the privately insured, which are the marginal effects estimated from the generalized linear models.

We analyzed the effect of insurance status before age 65 years on annual Medicare expenditures and the number of visits using all person-year data available. Control variables include dummies for gender, marital status, race/ ethnicity, education, family income categories, survey year, age, nine census divisions, and health status (1=excellent to 5=poor) at baseline. Some analyses using NHIS–Medicare control for state fixed effects, and some using the HRS control for supplemental insurance beginning at age 65 years and detailed baseline health status measures. The additional health measures include the comorbidities of depression, arthritis, cancer, diabetes, heart problems, high blood pressure, lung disease, or psychiatric problems; the number of limitations to the activities of daily living; the instrumental activities of daily living; current smoking; and drinking frequency.

Relative to the privately insured, we also analyzed the difference in the use of healthcare services for those uninsured by age _65/66, 67/68, and 69+ years to see if any differences decline over time. All analyses account for the possibility of the nonindependence of observations within HRS and NHIS sampling units using STATA Version 10 (StataCorp, 2007).

Because the fraction of the near elderly who agreed to give personal information necessary to match survey data to Medicare records may not be a random sample of survey respondents, we multiplied the HRS and the NHIS sample weights by the inverse of the probability that a record in the sample matches with Medicare records (Curtis et al., 2007). Because the attributes of matches and nonmatches may differ by insurance status, we estimated the probability of match stratified by insurance status. We used logistic regression to estimate the predicted probability of match and to adjust the HRS and NHIS survey weights.

Because there has been one other piece of research published on this topic using the HRS, we also performed sensitivity analysis to assess the reasons behind the difference between our results and the results in the other work (McWilliams et al., 2009). We explored both differences in the definition of who is included in the sample of privately insured and uninsured individuals and differences in analysis technique.

4 Results

Table A1 shows the attributes of individuals in the HRS and NHIS who match and do not match to Medicare records. In both surveys, individuals who are publicly insured before age 65 years are more likely to match to Medicare records compared with individuals with other insurance status before age 65 years. In both surveys, individuals in poor health are more likely to match to Medicare records than individuals not in poor health. As described in the Methods section, we predicted the probability of a match to Medicare records stratified by insurance status before age 65 years as a function of survey characteristics. We then multiplied the HRS and the NHIS survey weights by the inverse of the predicted probability of a match. Table I reports attributes of the NHIS–Medicare and HRS–Medicare analysis samples by insurance status before age 65 years using these weights. Uninsured individuals before age 65 years in both surveys are more likely to have less than 12 years of education and a family income less than $20,000 than those with private insurance. They are also more likely to be non-White and in fair or poor health.

Table II summarizes unadjusted and adjusted differences in Medicare expenditures and other measures of the use of Medicare-covered services after turning 65 years old according to insurance status before age 65 years. There are no statistically significant differences in Medicare expenditures or in the number of hospitalizations after age 65 years between those who were uninsured before age 65 years and those who were privately insured. However, those publicly insured before age 65 years have substantially higher expenditures than those privately insured. In the final column of Table II, results from the HRS indicate that individuals who were publicly insured before age 65 years have Medicare expenditures that are approximately 30% higher than those who were privately insured even after adjusting for supplemental coverage after age 65 years and a large number of observed health characteristics before age 65 years.

Although individuals who were previously uninsured do not have statistically significantly different Medicare expenditures or hospitalizations compared with those who were previously privately insured, they do have statistically significantly fewer physician visits. Results from the NHIS indicate that the previously uninsured have about two fewer visits per year compared with the previously uninsured. Although not reported in the table, this result is nearly identical (-1.91, SE=0.45) if controls for census region are replaced by state fixed effects. The last column of results from the HRS indicates that when controlling for supplemental insurance beginning at age 65 years and a more detailed set of baseline health measures, the previously uninsured. Have approximately 0.7 fewer visits per year compared with the previously privately insured, a difference of approximately 11% relative to the mean number of visits among the previously insured (approximately 6.5 per year). The previously publicly insured have approximately 0.84 more visits compared with the previously privately insured, a difference of approximately 13%.

Table III examines physician service use by insurance status before age 65 years in more detail. Considering the last column of the table adjusting for supplemental coverage after age 65 years and a wide variety of controls for baseline health status, results indicate that individuals who were previously uninsured have approximately 16% fewer visits to office-based physicians than those who were previously insured. However, they have approximately 43% more visits to hospital outpatient departments and approximately 18% more visits to hospital emergency departments.

Table IV reports the differences in the use of health services for individuals who were privately insured compared with those who were uninsured by age. The pattern of differences in expenditures and hospitalizations between the previously uninsured compared with the privately insured is not clear. Results from the HRS seem to show that the previously uninsured have fewer physician visits compared with the previously uninsured right after the age of 65 years, but this difference dissipates at older ages. This might suggest that the previously uninsured change their pattern of healthcare consumption slowly upon reaching the age of 65 years. This might also be some evidence of pent up demand for the previously uninsured who may temporarily decrease their use of health care before age 65 years in anticipation of coverage at age 65 years. However, the evidence of pent up demand is not strong because physician visits for the previously uninsured are lower rather than higher right after age 65 years than those for the previously privately insured. Also, results from NHIS show no decline in the lower use of physician care among the previously uninsured by age, and results for the HRS are imprecise for 69 years and older.

Table V summarizes some differences between our HRS–Medicare analysis and that presented by McWilliams et al. (2009). The first column of the table repeats our basic result from Table II. The second column changes the categorization of insurance. McWilliams et al. (2009) defined the "continuously or intermittently uninsured" as those who were uninsured in 1992 or at any subsequent time in the survey. The "uninsured" in the second column of the table adopts this definition of "uninsured," although it excludes those who transition from uninsured in 1992 to public insurance in any subsequent wave. McWilliams et al. (2009) defined the insured as those who never experience any lack of insurance in any wave, except those who were publicly insured in 1992. Again, the second column of Table V adopts this definition of "privately insured," except it excludes those who transferred from private insurance in 1992 to public insurance in any subsequent wave. Results in column 2 continue to find no statistically significant difference between the uninsured and the insured in total Medicare expenditures and show that the uninsured have statistically significantly fewer physician visits compared with the insured.

Because it is possible that the uninsured live in areas with lower Medicare spending than the insured, column 3 of Table V adds controls for stratum effects, yielding results that are very similar to those in column 2. The fourth column of Table V, which adjusts only for stratum indicators, is an intermediate step that allows for assessing the effect of adjustments for baseline risk. The baseline risk adjustment used in this article, column 3, moves the estimates substantially from column 4, suggesting that those selecting into the uninsured group are at greater baseline risk for expenditures, inpatient stays, and physician visits. However, when the baseline risk adjustment used in the McWilliams et al. (2009) article is added, as displayed in column 5, the estimates are nearly identical to column 4. This comparison suggests that those selecting into the uninsured group are at the same baseline risk for expenditures, inpatient stays, and physician visits. The baseline risk adjustment in McWilliams et al. (2009) involves a complex set of procedures aimed at eliminating the aspects of baseline risk that could be attributed to periods of being uninsured. Ultimately, this baseline risk adjustment is achieved through an inverse probability weight rather than through covariate adjustment. Given that the selection mechanisms that could lead to the periods of lacking insurance in this age group tend to move the higher risks into the uninsured group, it seems that the risk adjustment method of McWilliams et al. (2009) does not reflect these differences.

Because McWilliams et al. (2009) did not exclude those who transition into public insurance, we considered the effect of this choice starting with the sixth column of Table V where those who transition to public insurance from uninsured or privately insured in 1992 were added to the sample. This adds 18% to the sample of the uninsured and 12% to the sample of the insured. Adding these individuals who transferred to public insurance to the sample doubles the estimated excess Medicare spending for the uninsured relative to the insured. Column 7 shows that results are virtually identical whether the inverse-probability weighting from McWilliams et al. (2009) is applied. This highlights the inadequacy of the McWilliams et al. (2009) risk adjustment because we expected some movement between columns 6 and 7, given the known selection among those at risk for high expenditure into uninsured among those who ultimately transition into public insurance before turning 65 years old. Finally, we note that our original results are still robust within this larger sample, given that the results in column 8—where we applied our baseline risk adjustment—look very similar to the results in columns 1 and 2. In summary, the sensitivity analysis in this section suggests that the differences between our results and those of McWilliams et al. (2009) are related to how those publicly insured before age 65 years are treated and to the use of appropriate baseline risk adjustment.

5 Discussion

This study uses Medicare claims data to examine the use of Medicare services beginning at age 65 years as a function of previous insurance status as measured from two different surveys—the NHIS and the HRS. We find that the previously uninsured have fewer physician visits than the previously insured. Although we know that insurance reduces financial barriers for accessing medical services (Decker, 2005; McWilliams, et al. 2007; Card et al., 2008) and Medicare at age 65 years increases the use of doctor visits and hospital stays for the previously uninsured (McWilliams et al. 2007), Medicare coverage may not be sufficient for the previously uninsured to use health services in the same way as those who are accustomed to accessing the healthcare system with insurance.

The previously uninsured use fewer outpatient office visits of all types, but they use more hospital outpatient department and emergency room visits compared with the previously insured. It is possible that there are the unmeasured characteristics of the uninsured that can explain these differences. For example, we cannot control for the proximity or availability of office-based physician services or other factors related to the use of services that may be correlated with being uninsured, such as one's predilection for health care. In addition to insurance coverage, previous research suggests that access barriers such as inadequate transportation, language barriers, and lack of awareness of healthcare options can affect the use of services for low-income populations (Gresenz et al., 2007; Felland et al., 2009).

We find no statistically significant difference in Medicare expenditures after turning 65 years old according to insurance status before age 65 years. Previous research has shown that health spending for the uninsured before age 65 years is lower than for the insured (Hadley, 2003). Although previous research also suggests that the previously uninsured increase their use of health services upon becoming insured at age 65 years (Decker, 2005; McWilliams et al., 2007; Card et al., 2008), this increase does not seem large enough that the previously uninsured end up with higher expenditures beginning at age 65 years compared with the previously insured.

McWilliams et al. (2009), who also used the HRS to consider the relationship between the insurance status before age 65 years and the use of health services after age 65 years, found that the previously uninsured had higher expenditures after age 65 years compared with the previously insured. They used this finding to suggest that insuring the uninsured earlier would avert this higher spending. In contrast, by using Medicare claims data linked to survey data from two different surveys, our results do not show statistically significant differences in expenditures after age 65 years for the previously uninsured compared with the insured and less use of physician care. As we have shown, the difference in the results lies in the previous work's disproportionate inclusion of the publicly insured in the uninsured group as well as their baseline risk adjustment that did not adequately account for observable differences in baseline risk between the insured and the uninsured groups. There is also a difference in interpretation. Because there are likely to be remaining unobservable differences between the uninsured and the privately insured before age 65 years (Bhattacharya, 2009; Polsky and Decker, 2010) we do not agree with the interpretation of McWilliams et al. (2009) on the measured differences in the use of Medicare services for the previously uninsured relative to the previously insured being an estimate of use that could be avoided if the previously uninsured were to be offered public insurance earlier.

There are limitations to our work. First, not all subjects in the HRS and NHIS were matched to their Medicare claims. Although we address this issue with reweighting, it may be the case that the pattern of matches may differ between the previously uninsured and the insured in ways that we were unable to measure. Second, the nonexperimental nature of our data limits our ability to identify any causal implications of coverage for the previously uninsured. As mentioned earlier, the previously uninsured are different than the previously insured for reasons that are not fully measured in survey data, and no type of covariate adjustment can fully address this limitation. Finally, our analysis suggests that providing insurance coverage to individuals aged 65 years or older does not seem to completely change their patterns of use of health care. Studies that examine the effects of the provision of health insurance on the patterns of the healthcare use of younger individuals would be useful to assess whether there are differences in effects by age.

Although expanding insurance coverage to the uninsured is likely to expand access to healthcare services, the net cost of this expansion and the existence of cost offsets remain an open question. Sustaining and sufficiently financing any enacted healthcare reform may depend, in part, on whether cost offsets are ultimately realized. Evidence that cost savings result from better access to preventive care and treatment of chronic conditions is mixed (Cohen et al., 2008; Russell, 2009). Our findings offer suggestive evidence that there would be no short-term spending offset of expanding Medicare before age 65 years, given that we do not observe any spending differences between the previously uninsured and the privately insured. The fact that we show that not all differences between the previously uninsured and the privately insured dissipate after the age of 65 years supports this finding, as well as the probability that some differences between the insured and the uninsured are due to factors other than insurance status alone. Over the long term, it is possible that the previously uninsured would change their patterns of care. What we do find is evidence that for at least a few years, individuals who were uninsured before age 65 years seem to continue to use the healthcare system differently from those who were privately insured, relying less on outpatient care for their medical care.

A key question for the future may be why the previously uninsured seem to continue to use the healthcare system differently from the previously insured after the age of 65 years. Another question may concern the effect of the continued different use of the healthcare system by the previously uninsured. The effect of the different patterns of use of outpatient care on the quality of care and patient outcomes could be investigated. For example, previous work has grouped hospitalizations into several categories that are thought to be "avoidable" or "ambulatory care sensitive" in that effective outpatient care could reduce the risk of hospitalization by preventing or managing an illness (Billings et al. 1993). The effect of insurance status before age 65 years or the different patterns of use of outpatient care beginning at age 65 years on ambulatory care sensitive hospitalizations could be investigated. In any case, both health insurance coverage and other policies that facilitate access to physician services among the previously uninsured may be necessary to substantially alter their use of health care. This may be important to consider as health coverage expansions are debated and possibly implemented.

Table 1: Characteristics (Percent) of HRS and NHIS Records That Match to Medicare Records By Insurance Status Before Age 65

	NHIS-Medicare			HRS-Medicare		
	Uninsured	Publicly Insured	Privately Insured	Uninsured	Publicly Insured	Privately Insured
Attributes Before Age 65						
Female	59.9	53.0	52.7	57.4%	51.3%	50.3%
Married	55.4	63.3	79.6	60.8	56.7	79.3
Non-Hispanic Black	13.3	14.3	5.7	21.2	27.0	9.9
Hispanic	16.1	8.7	3.7	19.0	14.7	3.3
Non-Hispanic and Not Black or White	6.4	4.2	1.9	3.0	2.2	1.2
Less Than High School	48.2	36.6	16.3	48.8	48.9	16.5
High School Degree	29.8	32.1	38.5	33.2	34.1	41.9
Some College	13.0	20.0	24.0	10.4	11.9	20.1
Income < $20,000	69.1	68.9	46.6	51.6	57.8	11.6
Income >= $20,000, <$45,000	28.3	31.3	42.2	29.6	23.2	27.5
Health - Very Good	21.0	17.8	34.3	19.2	9.8	35.4
Health - Good	32.5	29.2	30.0	31.0	23.0	32.6
Health - Fair	21.4	25.1	8.8	28.0	34.8	13.1
Health - Poor	6.2	16.6	1.6	10.8	28.2	3.0

For the NHIS, the sample consists of 5,090 individuals (574 uninsured, 3,245 privately insured, and 1,271 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables.

For the HRS, the sample consists of 4,108 individuals (500 uninsured, 2,892 privately insured, and 716 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables.

Table II: Use of Medicare Services Beginning at Age 65 By Insurance Status Prior to Age 65

		Difference Relative to Privately Insured					
		Unadjusted		Adjusted		Adjusted Including Supplemental Insurance and Extra Health Controls	
	Mean for Privately Insured	Uninsured	Publicly Insured	Uninsured	Publicly Insured	Uninsured	Publicly Insured
NHIS-Medicare							
Expenditures	4,930.84	416.49	2349.22***	-609.40	504.79*	--	--
		[570.70]	[391.96]	[430.10]	[289.58]		
Inpatient Stays	0.20	0.08*	0.13***	0.02	0.04***	--	--
		[0.04]	[0.02]	[0.03]	[0.01]		
Physician Visits	7.29	-1.64***	0.94**	-2.02***	0.09	--	--
		[0.47]	[0.29]	[0.44]	[0.29]		
HRS-Medicare							
Expenditures	4,148.46	330.29	3274.15***	-88.50	1809.65***	-59.66	1275.52***
		[365.60]	[291.57]	[386.30]	[315.21]	[352.24]	[308.87]
Inpatient Stays	0.18	.07***	.19***	0.04*	.10***	0.04*	.07***
		[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Physician Visits	6.50	-0.38	2.57***	-1.07***	1.32***	-.70**	.84***
		[0.38]	[0.29]	[0.34]	[0.31]	[0.30]	[0.28]

Adjusted differences consist of marginal effects from a generalized linear model using a log link and, for expenditures, a gamma distribution and for visit/stay counts, a negative binomial. Standard errors are in brackets. Control variables for adjusted differences include gender, marital status, race, education and income categories, health status, dummies for census division, and year effects. Additional control variables in the final column include comorbidities of depression, arthritis, cancer, diabetes, heart problems, high blood pressure, lung disease, or psychiatric problem; ADLs; IADLs; current smoker; and drinking frequency. Supplemental insurance status includes those who reported in the wave after turning 65 having insurance through an employer or former employer, as an individual through a MediGAP plan, or with the government through Medicaid or the Veterans Administration.) The symbols *, ** and *** denote significance at the 10, 5 and 1% level respectively.

For the NHIS, the sample consists of 33,368 person years (3,490 uninsured, 22,405 privately insured, and 7,473 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.

For the HRS, the sample consists of 20,047 person years (2,398 uninsured, 14,589 privately insured, and 3,060 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.

Table III: Use of Phyician Services Beginning at Age 65 By Insurance Status Prior to Age 65

	Mean for Privately Insured	Difference (Uninsured - Privately Insured)		
		Unadjusted	Adjusted	Adjusted Including Supplemental Insurance and Extra Health Controls
NHIS-Medicare				
Physician Visits	7.29	-1.64*** [0.47]	-2.02*** [0.44]	--
Office-Based	6.67	-2.42*** [0.42]	-2.37*** [0.39]	--
General	3.07	-0.34 [0.24]	-0.64*** [0.19]	--
Specialist	3.10	-0.62*** [0.09]	-1.39*** [0.27]	--
Other and non-physician	0.50	-0.20** [0.09]	-0.13** [0.06]	--
Hospital Outpatient Department	0.33	0.39*** [0.09]	0.17** [0.08]	--
Emergency Room	0.29	0.20*** [0.05]	0.08* [0.04]	--
HRS-Medicare				
Physician Visits	6.50	-0.38 [0.38]	-1.07*** [0.34]	-.70** [0.30]
Office-Based	6.03	-1.10*** [0.35]	-1.39*** [0.31]	-.97*** [0.28]
General	2.69	-0.35* [0.19]	-.70*** [0.18]	-.53*** [0.17]
Specialist	2.87	-.58** [0.28]	-.42* [0.26]	-0.21 [0.23]
Other and non-physician	0.48	-.18** [0.07]	-.21*** [0.06]	-.17*** [0.05]
Hospital Outpatient Department	0.30	.41*** [0.07]	.15** [0.07]	.13** [0.06]
Emergency Room	0.17	.10*** [0.02]	.03** [0.02]	.03** [0.01]

"Publicly Insured" category included but not shown.

Adjusted differences consist of marginal effects from a generalized linear model using a log link and, for expenditures, a gamma distribution and for visit/stay counts, a negative binomial. Standard errors are in brackets. Control variables include those listed in Table 2. The symbols *, ** and *** denote significance at the 10, 5 and 1% level respectively.
For the NHIS, the sample consists of 33,368 person years (3,490 uninsured, 22,405 privately insured, and 7,473 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.
For the HRS, the sample consists of 20,047 person years (2,398 uninsured, 14,589 privately insured, and 3,060 publicly insured) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.

Table IV: Use of Medicare Services Beginning at Age 65 By Age and Insurance Status Prior to Age 65

		Difference Relative to Privately Insured					
		Adjusted			Adjusted Including Supplemental Insurance and Extra Health Controls		
	Mean for Privately Insured	Uninsured Ages 65-66	Uninsured Ages 67-68	Uninsured Ages 69+	Uninsured Ages 65-66	Uninsured Ages 67-68	Uninsured Ages 69+
NHIS-Medicare							
Expenditures	4,925.59	-70.79 [704.80]	-1280.95** [660.00]	-595.83 [472.56]	--	--	--
Inpatient Stays	0.20	0.00 [0.04]	0.01 [0.04]	0.03*** [0.03]	--	--	--
Physician Visits	7.29	-2.20*** [0.66]	-2.37*** [0.60]	-1.94*** [0.47]	--	--	--
HRS-Medicare							
Expenditures	4,148.46	-682.95* [411.78]	-523.62 [468.08]	1218.20 [834.36]	-599.61 [387.88]	-492.24 [422.26]	1168.16 [782.92]
Inpatient Stays	0.18	0.00 [0.02]	0.04 [0.03]	.10** [0.05]	0.00 [0.02]	0.04 [0.03]	.10** [0.05]
Physician Visits	6.50	-1.73*** [0.33]	-0.97*** [0.37]	0.04 [0.35]	-1.44*** [0.31]	-0.69* [0.37]	0.48 [0.37]

"Publicly Insured" category included but not shown.

Adjusted differences consist of marginal effects from a generalized linear model using a log link and, for expenditures, a gamma distribution and for visit/stay counts, a negative binomial. Standard errors are in brackets. Control variables for adjusted differences include age, gender, marital status, race/ethnicity, education and income categories, health status, dummies for census division, and year effects. Additional control variables in the final column include comorbidities of depression, arthritis, cancer, diabetes, heart problems, high blood pressure, lung disease, or psychiatric problem; ADLs; IADLs; current smoker; and drinking frequency. Supplemental insurance status includes those who reported in the wave after turning 65 having insurance through an employer or former employer, as an individual through a MediGAP plan, or with the government through Medicaid or the Veterans Administration.) The symbols *, ** and *** denote significance at the 10, 5 and 1% level respectively.

For the NHIS, the sample consists of 33,368 person years (22,405 privately insured, 7,473 publicly insured, 960 uninsured at ages 65 or 66, 817 uninsured at ages 67 or 68, and 1,713 uninsured at ages 69+) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.

For the HRS, the sample consists of 20,047 person year (14,418 privately insured, 3,015 publicly insured, 862 uninsured at ages 65-66, 653 uninsured at ages 67-68, and 855 uninsured at ages 69+) who match with Medicare records, were under the age of 65 at the time of the survey, and have non-missing information on survey variables. The analysis also excludes those in an HMO once they enter an HMO and individuals in any year who do not have Part B for any month of the year.

Table V: Use of Medicare Services Beginning at Age 65 By Insurance Status Prior to Age 65: Sensitivity Analysis

	Difference Relative to Privately Insured							
HRS-Medicare								
Definition of "Uninsured"	At age 63 or 64	Always, Tranferred from Private Insurance in 1992 to Uninsured, or Transferred from Uninsured in 1992 to Private Insurance				Left Plus Transitioned from Uninsured in 1992 to Public Insurance		
Definition of "Privately Insured"	At age 63 or 64	Always Privately Insured				Left Plus Transitioned from Private in 1992 to Public Insurance		
Column	(1)	(2)	*(3)*	(4)	(5)	(6)	(7)	(8)
McWilliams et al. (2009) inverse probability weighting	No	No	No	No	Yes	Yes	No	No
Adjusted for covariates in Table 2	Yes	Yes	Yes	No	No	No	No	Yes
Adjustment includes stratum effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Expenditures	-88.50	-443.15	-334.37	579.19**	601.91**	1146.69***	1127.21***	-42.16
	[386.30]	[289.01]	[293.34]	[273.63]	[272.44]	[287.51]	[287.53]	[293.47]
Inpatient Stays	0.04*	-0.01	-0.01	0.04***	0.04***	0.05***	0.05***	0.00
	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Physician Visits	-1.07***	-0.53***	-0.56***	-0.21*	-0.12	0.01	-0.07	-0.52***
	[0.34]	[0.14]	[0.13]	[0.13]	[0.13]	[0.12]	[0.12]	[0.13]
Person years uninsured	2,398	4,918	4,918	4,918	4,918	5,749	5,749	5,749
Person years insured	14,589	15,527	15,527	15,527	15,527	15,527	15,527	15,527

Adjusted differences consist of marginal effects from a generalized linear model using a log link and, for expenditures, a gamma distribution and for visit/stay counts, a negative binomial. Standard errors are in brackets. Covariates from Table 2 include gender, marital status, race, education and income categories, health status, dummies for census division, and year effects.

Although not reported, analyses in the first column of this table include a separate category for those publicly insured at ages 63 or 64, and analyses in subsequent columns include a separate category for those publicly insured in 1992.

Appendix Table 1: Characteristics (Percent) of HRS and NHIS Records That Match or Do Not Match to Medicare Records

	NHIS-Medicare			HRS-Medicare		
	Match	No Match	P-value	Match	No Match	P-value
Attributes Before Age 65						
Uninsured	9.1	11.5	<0.01	13.2	7.5	<0.01
Publicly Insured	20.3	11.9	<0.01	16.9	6.3	<0.01
Female	52.3	52.3	0.92	54.2	51.0	<0.01
Married	73.8	75.1	0.03	70.6	72.2	0.17
Non-Hispanic Black	8.6	9.9	<0.01	8.7	11.2	<0.01
Hispanic	7.3	6.3	<0.01	6.3	8.1	<0.01
Non-Hispanic and Not Black or White	4.0	2.8	<0.01	2.1	2.6	0.19
Less Than High School	20.1	25.0	<0.01	22.2	23.5	0.24
High School Degree	36.7	37.9	0.07	39.4	37.5	0.10
Some College	21.7	25.2	<0.01	19.5	19.9	0.66
Income < $20,000	20.3	26.4	<0.01	22.3	21.9	0.66
Income >= $20,000, <$45,000	35.9	38.9	<0.01	27.4	24.0	<0.01
Health - Very Good	25.4	29.6	<0.01	31.0	30.1	0.45
Health - Good	30.0	28.8	0.28	30.0	33.3	0.03
Health - Fair	11.2	15.2	<0.01	17.4	15.1	<0.01
Health - Poor	7.7	4.7	<0.01	7.6	6.1	0.03

For the NHIS, the sample consists of 9,588 individuals who are under the age of 65 at the time of the survey, turn 65 before January 1, 2000, have non-missing information on survey variables and are not on public insurance at the time of the survey.
For the HRS, the sample consists of 9,227 individuals who are under the age of 65 at the time of the survey, turn 65 before January 1, 2004, have non-missing information on survey variables and are not on public insurance at the time of the survey.
P-value refers to the value associated with the difference between those who match or do not match with Medicare based on a Wald F test.

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