Long-term Consequences of Short-term Precipitation Shocks: Evidence From Brazilian Migrant Households

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Abstract

We find that large short-term precipitation shocks damage the long-term income of households that have permanently migrated from rural to urban areas. This outcome is consistent with the behavior of credit-constrained rural households who are willing to accept lower long-term income in urban areas following the depletion of their productive assets during an adverse shock. The acceptance of lower income persists into the long-term, as long as mechanisms for rebuilding capital remain unavailable. Our empirical evidence suggests that there may be a link between large precipitation shocks in rural areas and urban poverty. Further exploration is warranted on the mechanisms by which natural disasters cause these long-term losses.

JEL Classification: O1, Q1, R2
Key words: Climate, shocks, agriculture, household income, migrants

1 Introduction

Droughts and floods are particularly damaging in low-income countries, affecting the livelihoods of both rural and urban households. Scientific predictions indicate that these events

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may only increase with global warming (Dai et al., 2004). An inability to effectively reduce shock-induced income loss can lead to severe long-term consequences for households in developing countries. For example, precipitation shocks may directly destroy assets necessary for agriculture. Alternatively, households may liquidate assets to smooth income, thus reducing their future earning potential. Without formal insurance arrangements, savings, or credit markets, rural households in developing countries are particularly vulnerable to the income variability induced by precipitation anomalies, leaving migration as one of the few viable risk mitigation options. In fact, Barrios et al. (2006) have empirically linked the decline in rainfall with a rise in urbanization in sub-Saharan Africa.

We find the first evidence that these climate-driven rural processes negatively impact urban migrants' wages in the long-term. Specifically, we detect a long-term negative impact of past large precipitation shocks on the current income of Brazilian rural households that migrated to urban areas permanently (as opposed to seasonally). We focus on migrants in order to identify the effect of large precipitation shocks in the long-term using a cross-section of households. By exploiting variation in migration timing, destination, and origin, we are able to include a series of fixed effects to control for unobserved heterogeneity.

We motivate one explanation for why migrants might experience income losses following a large shock. After a household loses agricultural capital, urban income that was once unacceptably low may become attractive. Following a shock, households may prefer urban employment if they are unable to protect or replace the assets necessary to maintain agricultural income. These migrants are unable to earn greater income in urban areas over the long-term due to the lack of capital stock for human or physical capital investment. Evidence of long-term climate-related damages to agricultural productivity is revealed through the income of households that migrate out of agriculture. Our findings suggest that limited opportunities for rural households to manage climate-induced income risk may lead to an increase in urban poverty.

A large literature has analyzed the ability of households to smooth consumption when facing shocks to productivity and income (Zeldes, 1989; Deaton, 1991, 1992; Paxson, 1992; Alderman and Paxson, 1994; Townsend, 1994). Recent studies have shown that households are unable to smooth consumption completely, even when informal insurance arrangements are available (Jalan and Ravallion, 1999; Kazianga and Udry, 2006). A related literature asserts that a lack of credit institutions leads low-income households, facing shocks to productivity, to invest in less risky portfolios which reflects their limitations in smoothing consumption. Moreover, these conservative portfolio choices can perpetuate the inequitable distribution of income, as risky portfolios on average yield higher returns (Eswaran and Kotwal, 1990; Rosenzweig and Binswanger, 1993; Rosenzweig and Wolpin, 1993). Our paper takes this discussion further by assessing the long-term consequences, if any, of incomplete consumption smoothing. In addition, previous findings are based on localized surveys. If these impacts are systematic and widespread, they should surface in national household datasets. To our knowledge, we are the first to find evidence of these long-term drought consequences using a nationwide household survey.

We use the 1995 Brazilian national household survey to measure the income impact of short-term precipitation shocks. Specifically, we exploit information on households who migrated from predominantly rural states to cities within the past nine years of the survey to observe the impact of past shock-induced productivity losses on current household income. In a household income regression, we include variables on ex ante risk (the mean and variance of the distribution of precipitation in a migrant's place of origin) and ex post risk (the precipitation shock variables) to differentiate between households that use migration as a temporary coping strategy, and credit-constrained households forced to permanently migrate, perhaps due to the severity of the shock on their agricultural production and assets.

Our empirical findings reveal that there may be significant damage to a household's agricultural earning potential due to large precipitation shocks. Although many households may successfully migrate to urban environments to improve their incomes, we find evidence that others appear to have lower incomes after migrating. One characterization of the latter group is farmers who migrate as a method of last resort because of losses in their productive assets, accepting lower incomes in the short-term to satisfy basic needs *and* in the long-term due to their inability to rebuild capital in subsequent years. In the next section, we outline a simple conceptual model to illustrate how large precipitation shocks may affect the rural-urban location choice, and offer an explanation for why losses may appear in migrants' urban incomes.

2 The Link Between Climate-Driven Rural-Urban Location Choice and Migrants' Income Losses

We present a basic household production model to motivate why incomes of households that permanently migrated from rural to urban areas might reveal long-term agricultural productivity damage from large precipitation shocks. Consider a risk-neutral household that has a choice between two locations, a rural location where income is derived from agricultural activities and an urban location where income depends on non-agricultural activities. At the beginning of the planting season (before knowing the upcoming precipitation), the household compares the expected income between locations, and selects the location with the highest income net of moving cost.

Let z denote annual precipitation, and the function $f(z)$ represent household beliefs regarding the probability density of z. The mean and variance of z are denoted as μ_z and σ_z^2. Let $\boldsymbol{x}$ be a vector of household characteristics, $\boldsymbol{p}$ be a vector of input and output prices, k represent a household's capital endowment, and $l \in \{r, u\}$ index location. Rural is determined by the function $\pi_r(z, k, \boldsymbol{x}, \boldsymbol{p})$. Urban income is independent of climate and represented by the function $\pi_u(k, \boldsymbol{x}, \boldsymbol{p})$. Note that household income is a function of capital, which can be in the form of human capital or productive assets.

We assume productivity of capital differs for rural and urban locations in the following way. Figure 1 illustrates under what circumstances each location may be more profitable, depending on the capital endowment. Households with an endowment between $\underline{k}$ and $\overline{k}$ select employment in the rural area, while those with capital above $\overline{k}$ or below $\underline{k}$ choose to work in the urban area. At very low levels of capital, shown in Case I, households are unable to sustain agricultural production, leaving low-paying wages in the urban sector as the only option. Households whose assets have been destroyed by a severe shock are also included in this case. Case II reflects the notion that only households with sufficient capital can be more productive in the rural location. For example, a dairy farmer must have the resources to invest in at least one cow to profit from dairy farming. Finally, Case III includes households with substantial capital who are able to exploit opportunities in the urban sector to earn high wages.

In this context, the household optimization problem is to choose the location to maximize expected income:

$$\max_{l \in \{r,u\}} \left\{ E\left[\pi_r\left(z, k, \boldsymbol{x}, \boldsymbol{p}\right)\right], \pi_u\left(k, \boldsymbol{x}, \boldsymbol{p}\right) - m \right\}, \tag{1}$$

where m indicates moving costs.

Whereas capital determines where expected income is greater, past climate affects a rural household's current level of capital. During a severe shock, households may lose productive assets, or need to liquidate capital to maintain a minimal level of consumption. Small shocks are less problematic. Capital is not physically destroyed for small deviations from the mean precipitation level. Households are also able to tolerate small consumption losses and mitigate marginal impacts on productive assets using whatever limited savings are available. We approximate this idea by assuming k is concave in z and $\frac{\partial k}{\partial z}|_{\mu_z} = 0$.

Let z_0 denote last year's precipitation level, and k_0 denote last year's capital stock. Define

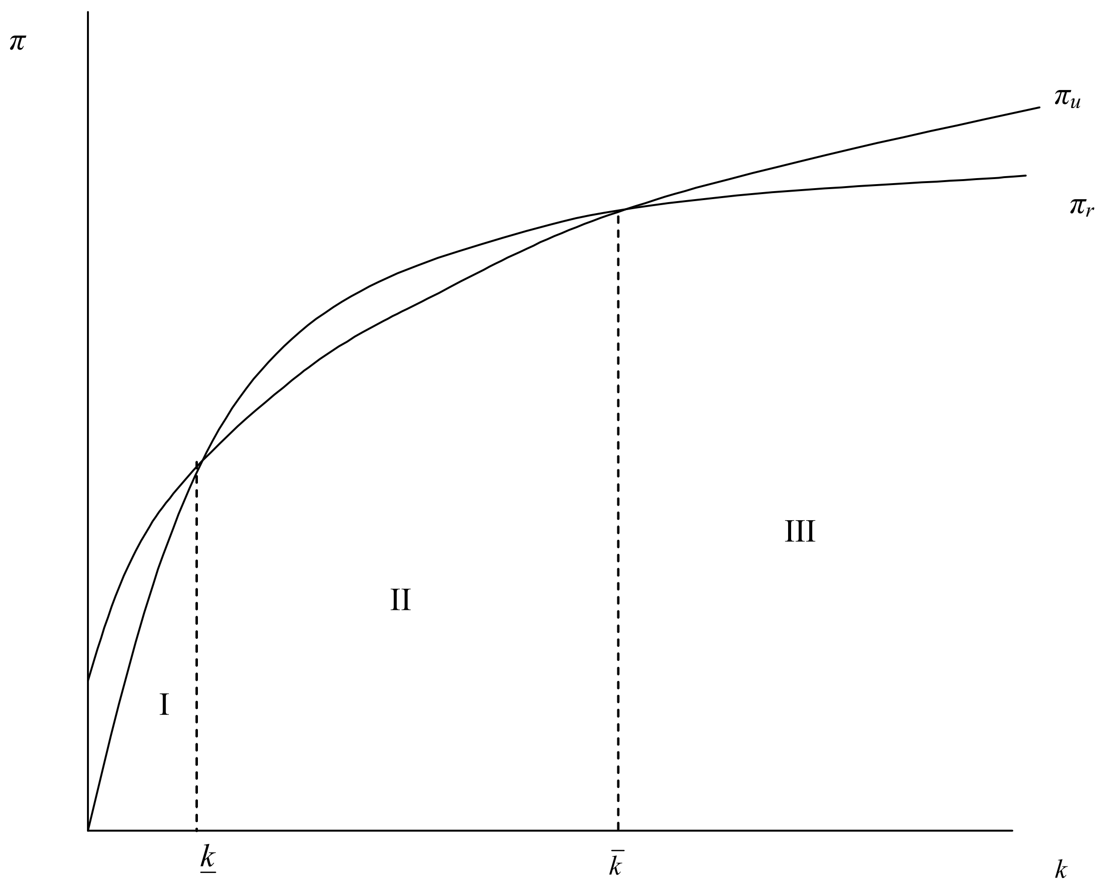

Figure 1: Relationship Between Capital Endowment, Agricultural Rural Income, and Non-Agricultural Urban Income

the precipitation shock $\Delta z \equiv \mu_z - z_0$, as the deviation in precipitation from the average. We can express rural income as $\pi_r(k(k_0, z_0))$, suppressing the other arguments of the income function. We approximate π_r with a Taylor series expansion around μ_z:

$$\begin{array}{l} \pi_r\left(k(k_0, z_0)\right) \approx \pi_r\left(k(k_0, \mu_z)\right) - \frac{\partial \pi_r}{\partial k}\frac{\partial k}{\partial z_0}|_{z_0=\mu_z}\left(\Delta z\right) \\ +\frac{1}{2}\left[\frac{\partial \pi_r}{\partial k^2}\left(\frac{\partial k}{\partial z_0}|_{z_0=\mu_z}\right)^2 + \frac{\partial \pi_r}{\partial k}\frac{\partial^2 k}{\partial z_0^2}|_{z_0=\mu_z}\right]\left(\Delta z\right)^2 \end{array}. \tag{2}$$

The change in rural income due to the shock is then

$$\Delta \pi_r \equiv \pi_r\left(k(k_0, z_0)\right) - \pi_r\left(k(k_0, \mu_z)\right) \approx \frac{1}{2}\frac{\partial \pi_r}{\partial k}\frac{\partial^2 k}{\partial z_0^2}|_{z_0=\mu_z}\left(\Delta z\right)^2. \tag{3}$$

The reduction in expected rural income from a precipitation shock impacts the location decision for households with endowments between $\underline{k}$ and $\overline{k}$ since urban income becomes relatively more attractive. After a shock, the household has a lower expected rural income and is willing to accept lower urban income due to its loss of productive assets.

3 Data

We use the 1995 Pesquisa Nacional de Amostra Domicílios (PNAD), an annual nationwide household survey administered by the Brazilian government in which each year is an independent cross-section. The PNAD questionnaire collects information regarding demographics, wages, housing, and migration for each member of the households sampled. This information is georeferenced to the municipality level, analogous to a U.S. county, using Brazilian GIS data (IBGE, 1998). The survey data indicates the destination of a migrant, i.e., the municipality in which the migrant was surveyed. However, the information regarding previous locations of migrants is limited by the survey design. Households were asked if they migrated, how many years ago, and from what state they were born and migrated from (not the municipality).[1]

To formulate our climate variables, we use the National Oceanic and Atmospheric Administration, National Centers for Environmental Prediction, Climate Prediction Center global precipitation data product (Xie and Arkin, 1996, 1997). This source uses a combination of weather station observations, satellite estimates, and numerical model predictions to provide a comprehensive georeferenced grid of precipitation indicators at a 2.5 degree spatial resolution. The resolution is at a convenient scale for our state and municipality level census data. Monthly data begins in 1979. In Brazil, this incorporates a great deal of weather station data (from 13,197 stations).[2]

Figure 3 is a map of Brazil and decomposes the country into five regions, North (N), Northeast (NE), Southeast (SE), South (S), and Midwest (MW). Figures 4 and 5 present the long-term climate distributions across Brazil. They also illustrate the scale of the 2.5 degree pixel. Climate pixel data were spatially averaged using state boundaries, also consistent with the reporting of migrants' origins at the state level. Climate data mean, variance, and spatial aggregation operations were performed through queries to the IRI Data Library web interface.[3] In Figure 4, it is clear that the Amazonian Northwest has some of the wettest areas in Brazil, and the Northeast has some of the driest areas. The Northeast also experiences substantial variation in precipitation (see Figure 5).

In the analysis, we focus on rural households that migrated to urban areas within the last nine years of the 1995 survey. Approximately 85,000 households were sampled in the 1995 survey. Data regarding which state migrants lived in previously is available for this group (not the municipality). There are several migration patterns in Brazil (e.g., rural to rural,

[1] The survey asks individuals if they were born in the municipality in which they are currently living. Thus, the birth municipalities of individuals that reported being born in their municipality of residence is known. Additionally, the survey asks the individual if he migrated from another municipality in the current state of residence, without having him report name of the municipality.

[2] Agência Nacional de Energia Elétrica (ANEEL), http://ingrid.ldeo.columbia.edu/SOURCES/.ANEEL

[3] http://iridl.ldeo.columbia.edu.

rural to urban, urban to rural, and rural/urban to Amazon) and several motivations for the various choices of migration. For clarity, we focus on rural to urban migration. We further restrict the sample to households currently living in urban areas. Urban areas are defined as municipalities with populations above one hundred thousand. We also limit the migrants in the analysis to those who came from predominantly rural states. A state is declared rural if its percentage of the population living in rural areas is above twenty-five percent. This leaves 40,005 households, 2,339 of which migrated between one to nine years prior to the survey.[4]

Table 1 compares the demographic characteristics of migrants and non-migrants in the 1995 PNAD dataset. There are few differences between these two groups. The composition of the households differs. Migrant households tend to have younger male household heads with more children than sedentary households. They also possess fewer assets, but their monthly income is slightly larger than non-migrants. One notable feature of this group is that they tend to come from places where the precipitation variation is slightly greater. This provides preliminary evidence that there may be migrants who manage income risk by moving to areas where the risk is lower.

The descriptive statistics for the precipitation shock and shock-squared variables are also included in Table 1. Since our model focuses on an annual production cycle, a natural definition of the shock is the deviation from the mean of the realized value of precipitation the year prior to migration. A positive value of the shock variable implies a dry shock, and a negative value, a wet shock. The value of the shock variable depends on the year the household migrated and the place of origin. From Table 1, it appears that, on average, our sample of migrants faced normal to slightly drier-than-average climate prior to moving.

Table 2 exhibits the distribution of the origin and destination for migrant households.

[4] In an effort to focus on long-term migration effects, we do not consider households that migrated during the survey year.

Two noticeable patterns exist. First, most migrants come from the NE which is particularly vulnerable to dry spells. Second, of those coming from the NE, many migrate to the cities in the NE and SE regions.

A final consideration regards the timing of the survey and migration. Our sample of migrants traveled during the time frame of 1986 to 1994. The challenge we face in identifying the effect of climate-induced migration on differences in household income is the concurrent events of precipitation shocks and economic recessions. For example, there were five severe economic recessions in the period of 1987 to 1992 (Chauvet, 2002). Figure 2 shows the trend of the number of standard deviations above and below the precipitation mean by region. Precipitation trends are shown for the northern and southern regions to reflect their distinct regional stochastic responses to El Niño Southern Oscillation (ENSO).[5] From the figure, it is clear that there were quite a few dry periods during the economic recessions. We include region and time fixed effects in our empirical models to differentiate between the effects of recessions and precipitation shocks on household income differences.

4 Econometric Model

We use the household data to estimate regressions for total monthly income π per household h in their current location i. Our benchmark regression is the following:

$$\begin{aligned} \log \pi_{hi} \;=\; & \beta_0 + AGE_{hi}\beta_1 + \log \widehat{\pi}_{hj}\beta_2 + \overline{R}_j\beta_3 + \sigma^2_{R_j}\beta_4 + (\overline{R}_j - \boldsymbol{\delta}^t_h \mathbf{R}^t_{hj})\beta_5 \\ & + (\overline{R}_j - \boldsymbol{\delta}^t_h \mathbf{R}^t_{hj})^2\beta_6 + \beta^d_{hi} + \beta^o_{hj} + \beta^{do}_{hij} + \beta^t_{hj} + \varepsilon_{hij}. \end{aligned} \tag{4}$$

[5] Separate stochastic processes in the north and south (Grimm et al., 1998; Hastenrath, 2000) tend to generate seasonal precipitation responses to ENSO that are strongly negatively related between the northern and southern parts of Brazil (Moura and Shukla, 1981; Nogues-Paegle et al., 2002). On average, when ENSO drives a wet year in the one region of Brazil, it drives a dry year in the other.

Table 1: Descriptive Statistics of Demographic and Climate Variables for Migrant and Non-migrant households

Variable	Migrants Mean	Migrants Std. Dev.	Non-Migrants Mean	Non-Migrants Std. Dev.
Head of Household Characteristics				
Education	7.88	4.67	7.60	4.53
Age	36.49	12.02	43.54	13.42
Male	0.83	0.38	0.79	0.41
Household Characteristics				
Household size	3.82	1.79	4.05	1.87
Number of members less 10 years old	0.93	1.04	0.78	0.99
Homeownership	0.49	0.50	0.74	0.44
Own Washing Machine	0.28	0.45	0.35	0.48
Monthly Income (1995 Reais)	909.59	1175.67	898.66	1298.54
Distance Migrated (km)	1194.40	752.18		
Climate				
Precipitation mean (mm/day)	3.65	1.12	3.65	0.88
Precipitation variance (mm/day)	0.51	0.21	0.41	0.19
Precipitation shock (mm/day)	0.02	0.67		
Precipitation shock squared (mm/day)	0.45	0.68		
Observations	2,339		37,666	

Table 2: Percent of Migrant Sample by Origin and Destination

Destination	Origin North	Northeast	Southeast	South	Midwest	Total
North	5.22	4.23	0.64	0.81	0.51	11.41
Northeast	3.16	13.68	1.15	0.47	0.13	18.59
Southeast	1.97	20.69	9.49	4.49	0.81	37.45
South	0.98	1.15	0.98	7.01	0.51	10.63
Midwest	4.36	10.30	3.55	1.92	1.79	21.92
Total	15.69	50.05	15.81	14.70	3.75	

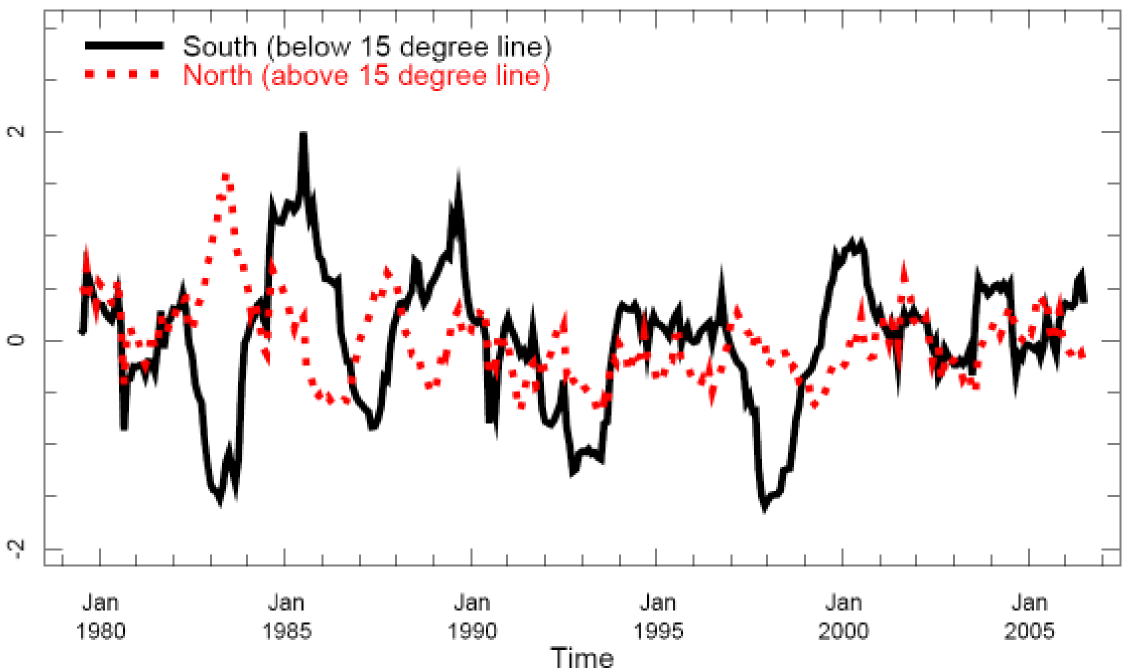

Figure 2: Standard Deviations of Precipitation by Region

We include exogenous household characteristic variables in the regression to control for idiosyncratic features of the household that may affect their current earnings. The head of household's age AGE_{hj} is a proxy for the head of household's stage in the life cycle. To control for differences in labor market opportunities across locations given the observable skill set of the household, we impute an income index. The income index $\log \widehat{\pi}_{hj}$ at the state of origin j is imputed from a monthly income regression that includes all workers over ten years old who were actively employed at the time of the survey.[6] Parameter estimates and standard

[6]Because some actively employed individuals do not report income, we estimate the wage regression accounting for sample selectivity using Full Information Maximum Likelihood (FIML) (see Greene, 1997). The Log-likelihood ratio test indicated that we can reject the null hypothesis that the correlation coefficient is equal to zero at the one percent significance level. The variables included in the selection equation are dummy variables indicating the age category of an individual, gender, the relationship to the head of household, receipt of pension, receipt of remissions, receipt of dividends or interest from investments, and regional dummy variables. OLS regressions ignoring sample selectivity were also estimated (results available on request). The R-squared was 0.52, indicating that a substantial fraction of the variation in wages is being captured in this regression.

errors are presented in Table 7 in the Appendix.[7] We use the parameter estimates to impute the potential income for individuals at their original location. We sum the imputed wages for all employed household members to control for monthly household income opportunities at its place of origin. Note that this control does not adjust for unobserved characteristics of households. Rather, the imputed income $\log \widehat{\pi}_{hj}$ is more effective in controlling for cross-sectional differences in labor markets between regions than for imputing the true incomes that a household might expect.

The precipitation mean $\overline{R}_k$ and variance $\sigma^2_{R_k}$ variables in the regression control for ex ante income risk. The precipitation shock $(\overline{R}_k - \boldsymbol{\delta}^t_h \mathbf{R}^t_{hk})$ and shock-squared $(\overline{R}_k - \boldsymbol{\delta}^t_h \mathbf{R}^t_{hk})^2$ variables capture the losses of the constrained households characterized in the theoretical model. These depend on the year the household migrated t and the place of origin j. $\boldsymbol{\delta}^t_h$ a row vector of dummy variables indicates the year a household migrated, and $\mathbf{R}^t_{hj}$ is a vector of precipitation values for municipality j in a given year t. Our model recognizes that some rural households may be quite capable of self-insuring against small shocks by liquidating or consuming their assets, but their coping strategies are limited for larger shocks. After losing assets, households may migrate to urban areas accepting a lower urban income because of the damage imposed on their local alternatives to agricultural production.

Regional destination β^d_{hj}, origin β^o_{hk}, and destination by origin β^{do}_{hjk} fixed effects, as well as time fixed effects β^t_{hk} capture the effect of unobservable spatial and time variables that influence current income. The spatial fixed effects are four dummy variables for the original location of each household, i.e. N, NE, S, and MW,[8] four dummy variables for the present location, and fifteen dummy variables that interact the regional dummy variables for the original and present locations.[9] Spatial fixed effects account for the effect of moving costs,

[7] To simplify the presentation of the wage equation parameters, we include the average and standard deviation of the parameters across twenty-seven states. All states except for São Paulo have a dummy to capture fixed effects.

[8] A dummy variable for the southeastern region is omitted from the regression.

[9] We omit the dummy variable that interacts the northeastern original location and northeastern current

migration networks (Munshi, 2003), and access to city amenities (Blomquist et al., 1988) on income. Time fixed effects capture competing shocks that may affect income-generating activities, such as a recession (von Wachter and Bender, 2006).

The last term ε_{hjk} in regression (4) represents the idiosyncratic error term. We bootstrap the standard errors (using 500 replications) for all specifications of model (4).

5 Identification and Results

Table 3 presents the results from our baseline regression. The shock-squared parameter is negative and significantly different from zero, supporting our hypothesis that large short-term shocks have long-term negative consequences on income. The magnitude of the shock parameter is close to zero and insignificant, implying that small wet and dry shocks have little measurable effect on long-term household income. Households may be somewhat able to cope with small unanticipated shocks so that they do not lead to long-term consequences. However, the shock-squared parameter reveals that a large shock does appear to cause long-term damage, perhaps from a loss of productive assets of the income of resource-constrained households.[10]

The parameters recovered for mean and variance of historical precipitation are also of interest. However, since they are included primarily as a control for observable climate information, are cross-sectional, and are recovered without careful effort to ensure identification, these results are suggestive at best. The effect of average precipitation is negative and marginally significant, while precipitation variance is positive and significant. This may indicate that those migrating from harsher (e.g., drier, more variable) climates do not necessarily represent the poorest groups, and may actually have developed skills that are valuable in

location dummy variables from the model.

[10] To confirm shocks are unanticipated, we estimate our wage regression including five additional variables for the shocks in the five years after the PNAD survey was conducted. Four out of five of these parameters were statistically insignficiant.

urban settings. The long-term migration process may yield greater household incomes for those more likely to face climate shocks as long as they are not migrating in response to losses arising from a severe climate shock.

Our baseline model also controls for what the present household would have earned in their original location by including an imputed wage variable. It is reassuring that the coefficient on the imputed income variable is close to one since we may expect the values of household characteristics to remain the same all else equal (e.g., excluding cost of living differences) if markets are competitive. The imputed income variable also substantially contributes to the variation of current incomes, as seen when comparing the R-squared values from the models that include and exclude the imputed income variable (see Table 3). Excluding the imputed income variable has little effect on the sign and importance of the shock-squared parameter, however.

To improve identification of the shock-squared parameter, we include a battery of additional confounding variables that may bias the shock variable parameters. We include regional origin, regional destination, regional origin by destination, and time fixed effects to absorb bias that may exist on the shock variable parameters. Table 8 in the Appendix displays the results from regressions that exclude spatial and time fixed effects, include only origin fixed effects, include only origin and destination fixed effects, and include only origin, destination, and origin by destination fixed effects. The results from these regressions are used to compare the impact of controlling for unobservable factors such as moving costs, migration networks, and limited access to city amenities, all having a potential positive impact on income. The results are fairly robust with the shock-squared parameter differing only slightly in magnitude and retaining significance across specifications. After controlling for spatial fixed effects, the magnitude of the shock-squared parameter estimates are slightly larger. The regression controlling for time-specific shocks yields a slightly smaller (in magnitude) negative and significant parameter on the shock-squared variable than in the fixed effect regressions in Table 8, although the time fixed effects are not jointly significantly different from zero in our baseline regression.

To avoid problems due to endogeneity, we used controls for auxiliary household characteristics that influence income in our baseline model. As a robustness check, we estimated additional specifications of the household income regression. One regression included eight dummy variables indicating the number of household members in a given age category, and the head of household's educational attainment. Another regression included the distances between the origin and destination states to proxy the impact of moving costs on household income. The results are presented in Table 9 in the Appendix. We include these only as diagnostics, since many of the household regressors are endogenous, and we lack suitable instruments for these variables.[11] Note the distance and distance-squared variable parameters are not statistically significant upon controlling for spatial fixed effects, perhaps because the spatial fixed effects act as an exogenous control for moving costs. Comparing the results across models, the specification of household characteristics does not affect our estimates of the impact of severe shocks on household income. In other words, the order of magnitude and significance of the shock-squared parameter is robust across specifications.

Chiswick (1999) examined the potential for migrants to self-select into more favorable labor markets. In contrast, our theoretical model characterizes a potential unfavorable selection problem. If our sample of migrants reflect low-income households that sort themselves into low-paid urban jobs in spite of long-term damage from shocks, then we must address that selection problem. There is some preliminary evidence to suggest that the migration patterns we observe are not simply the sorting of poor households. For example, the descriptive statistics for migrants do not support such a story. Instead of being poorer and less educated than non-migrants, the mean education and income of migrants is slightly higher. In addition, the mean and variance terms in the benchmark regression imply that

[11] Angrist and Krueger (1999) provide an in depth discussion of the endogeneity of education variables.

Table 3: Household Income Regressions

Variable	Baseline	Excluding Imputed Wage	Excluding Precipitation Mean, Variance
Intercept	0.5372***	6.4013***	0.4179***
	(0.1713)	(0.2099)	(0.1353)
Age	-0.0066***	0.0018	-0.0066***
	(0.0012)	(0.0019)	(0.0012)
Precipitation mean	-0.0570	-0.0607	
	(0.0358)	(0.0552)	
Precipitation variance	0.2526***	0.3849***	
	(0.0951)	(0.1369)	
Precipitation shock	-0.0004	-0.0503	-0.0031
	(0.0277)	(0.0414)	(0.0277)
Precipitation shock squared	-0.0664***	-0.0902**	-0.0492**
	(0.0253)	(0.0403)	(0.0250)
Log of imputed wage	0.9963***		0.9974***
	(0.0185)		(0.0184)
R-squared	0.59	0.05	0.59
Observations	2,339	2,339	2,339
Wald test: All coefficients=0	3658.13***	117.95***	3628.17***
Wald test: Shock variables=0	7.69**	5.48*	4.24
Wald test: Origin Fixed effects=0	8.77*	8.79*	8.84*
Wald test: Destination Fixed effects=0	2.45	7.34	3.24
Wald test: Origin×Destination Fixed effects=0	28.96**	38.52***	29.26**
Wald test: Time Fixed effects=0	7.81	0.51	7.37

1 Bootstrapped standard errors are in parenetheses. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

2 Regional destination fixed effects, regional origin fixed effects, fixed effects interacting regional destination and regional origin dummy variables, and time fixed effects are included in all wage model specifications.

migrants from drier, more variable climates may have higher incomes in urban areas, which is the opposite of what might be expected if the wage loss from a shock was driven by poor households sorting without long-term damage. Because these pieces of evidence are merely suggestive of the selection processes that may be occurring, we perform more diagnostics of potential bias from sample selection.

We test whether our shock variables are identifying the result of rural low-income households sorting into urban jobs due to short-term production impacts rather than the combination of long-term losses of productivity and lack of credit access prevalent in rural areas. In rural areas in Brazil, it is not uncommon for there to be a paucity of credit institutions, affecting all households. We are interested in providing evidence that our precipitation shock effect on income is not reflecting the tendency for migrants to be poor, but instead the impact of large shocks on productive assets and the inability of households to invest in human or physical capital in the long-term in urban areas. The possible bias that one may expect is affecting the shock-squared parameter is the effect of omitted variables associated with wealth. Suppose poorly educated households are responding to the adverse shocks by migrating. In this case, we would expect our parameter of interest to be negatively biased. To demonstrate the potential bias induced by factors related to wealth, we estimate our income regression replacing education and occupational status. The regression results reveal the shock variables are uncorrelated with factors related to wealth (see Table 4).

Realizing dry and wet shocks may have distinct impacts on household incomes, we estimated a model that includes five climate dummy variables (very dry, dry, normal, wet, and very wet) to determine if the size and sign of the shock influences the empirical results.[12] Normal climate was considered to be one standard deviation centered around the precipitation mean. The dummy variables dry and very dry were given a value of unity if the value

[12] Of the sample of migrants, 19.20, 8.38, 11.76, and 16.08 percent fell into the very wet, wet, dry, and very dry categories. The dummy variable that was omitted from the regression was classified as normal climate.

of the shock variable fell between 0.5 and 1 standard deviation above the mean, and greater than 1 standard deviation above the mean, respectively. The dummy variables wet and very wet were given a value of unity if the value of the shock variable fell between 0.5 and 1 standard deviation below the mean, and less than 1 standard deviation below the mean, respectively. Table 5 displays the results from this regression. When stratifying the shock variable in this manner, only the dry dummy variable parameter was significantly different from zero. Since the sign and order of magnitude of the impact of a dry shock is the same as that of the shock-squared term in previous regressions, it is likely that the parameter for the shock-squared term in the benchmark regression is largely driven by this category of shocks.

Our final model specification attempts to differentiate between the short-term and long-term impacts of precipitation shocks. The model includes variables that interact the shock variables, and dummy variables indicating whether the household migrated 1 to 4 years ago, and 5 to 9 years ago. The regression results are presented in Table 6.[13] We may consider it surprising that a significant effect on the shock-squared interacted with the Migrate 1 to 4 years ago parameter is not observed, since migrants would likely have relatively low rural income immediately following the shock. The only interaction that is significant is the shock squared interacted with the Migrate 5 to 9 years ago parameter, suggestive that the long-term (5-9 year) process does indeed appear to be driving our findings. The combined estimated effects of the short-term and long-term consequences of extreme climate, rather, corroborate our earlier claims. The findings suggest that migrant households fare better in urban areas than they would have had they stayed in rural areas in the short-term. However, in the long-term, these households are unable to invest to obtain the income they would have earned in rural areas when precipitation levels are normal. There are two possible factors contributing to the inability to invest in the long-term. First, these households abandon

[13] Diagnostic regressions were also performed that included interactions between the historical climate and shock variables (such as between the shock squared and the variance parameter). None of these interactions were significant.

the agricultural sector altogether to maintain short-term consumption following the shock, since there is no mechanism to endure the shock or rebuild the productive assets following the shock. The poverty trap literature identifies this outcome during the transition between economies (for example, migration costs) or the liquidation of assets lost in the transition process (such as badly defined rights for land or water) (Azariadis and Stachurski, 2006). Second, without capital, households are unable to make investments to improve their urban sector skills or succeed in generating equivalent or greater urban income. For example, a rural migrant interested in becoming a taxi driver must accumulate resources to obtain a license and car. Without capital, rural migrants will accept lower urban income in subsequent years following the shock to maintain their livelihood and out of the lack of economic alternatives.

6 Conclusion

Large precipitation shocks can damage households' productive capacities in rural areas. This has long-term negative impacts on migrants' urban incomes. Perhaps the loss is attributable to a reduction in the number of assets during large shocks, preventing households from continuing to work in rural areas. Since many of these households are credit-constrained, they are unable to weather the shock by borrowing or depleting savings. Households opt to work in urban locations to earn a lower long-term income, since it is more desirable than rural income immediately following the shock. Some of these households will continue to earn lower income because of lack of capital.

Using Brazilian household data, we observe some households facing these constraints. Our empirical evidence suggests that these households lose long-term income in rural areas because of short-term severe precipitation shocks. Although migrants face lower long-term income in urban areas, staying in their original locations may have led to an even worse outcome than urban migration. The observed decline in income may reveal the loss of worthwhile alternatives as opposed to damage from migration itself.

We use household economic and demographic information, and information regarding places of origin to identify these losses. Results provide insight to understanding the long-term damage to household welfare from large precipitation shocks in rural areas. Household data describing socioeconomic backgrounds before and after the shock would help improve the identification of climate-induced losses and allow for a direct test of the hypothesis posed in our conceptual model. If in fact losses are attributable to credit constraints, then policies that support increasing access to credit in rural areas may be appropriate for helping households endure large precipitation shocks.

Table 4: Regressions for Detecting Selection of Rural Migrants into Lower Paying Jobs

Variable	Shock-squared Parameter (Standard Error)	R-squared
Education	0.049	0.47
	(0.120)	
Occupational Status		
Armed forces	-0.004	0.05
	(0.007)	
Skilled agriculture and fishery workers	4.682E-4	0.03
	(0.006)	
Legislators, senior officials, and managers	0.004	0.05
	(0.011)	
Craft and related trades workers	0.005	0.09
	(0.018)	
Technicians and associate professionals	0.005	0.05
	(0.011)	
Clerks	0.002	0.02
	(0.006)	
Plant and machine operators	0.001	0.02
	(0.010)	
Service workers, and shop markets and sales workers	-0.015	0.03
	(0.014)	
Professionals	-0.005	0.12
	(0.011)	
Elementary occupations	0.001	0.08
	(0.014)	

1 Bootstrapped standard errors are in parentheses. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

2 Regional destination fixed effects, regional origin fixed effects, fixed effects interacting regional destination and regional origin dummy variables, and time fixed effects are included in all wage model specifications.

3 2,337 and 2,122 were included in the education and occupational status regression, respectively.

Table 5: Household Income Regression Including Very Dry, Dry, Wet, and Very Wet Dummy Variables

Variable	Parameter (Std. Error)
Intercept	0.5013***
	(0.1718)
Age	-0.0066***
	(0.0012)
Precipitation mean	-0.0422
	(0.0365)
Precipitation variance	0.2236**
	(0.0971)
Wet	0.0100
	(0.0510)
Very wet	-0.0584
	(0.0471)
Dry	-0.0917**
	(0.0451)
Very dry	-0.0408
	(0.0471)
Log of imputed wage	0.9964***
	(0.0184)
R-squared	0.59
Observations	2,339
Wald test: All coefficients=0	3735.55***
Wald test: Shock dummy variables=0	5.49
Wald test: Origin Fixed effects=0	7.83*
Wald test: Destination Fixed effects=0	2.61
Wald test: Origin×Destination Fixed effects=0	27.84**
Wald test: Time Fixed effects=0	7.47

1 Bootstrapped standard errors are in parentheses. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

2 Regional destination fixed effects, regional origin fixed effects, fixed effects interacting regional destination and regional origin dummy variables, and time fixed effects are included in the all wage model specifications.

3 Five climate dummy variables were generated to determine if the sign of the shock influenced the empirical results. The dummy variable that was omitted from the regression was classified as normal climate. Normal climate was considered to be one standard deviation of the shock variable centered around the mean. The dummy variables dry and very dry were given a value of unity if the value of the shock variable fell between 0.5 and 1 standard deviation above the mean, and greater than 1 standard deviation above the mean, respectively. The dummy variables wet and very wet were given a value of unity if the value of the shock variable fell between -0.5 and -1 standard deviation below the mean, and less than 1 standard deviation below the mean, respectively.

Table 6: Household Income Regression with Shock and Time Interaction Variables

Variable	Parameter (Std. Error)
Intercept	0.5493***
	(0.1706)
Age	-0.0066***
	(0.0012)
Precipitation mean	-0.0559
	(0.0357)
Precipitation variance	0.2487***
	(0.0949)
Precipitation shock×Migrate 1 to 4 years ago	-0.0702
	(0.0567)
Precipitation shock×Migrate 5 to 9 years ago	-0.0190
	(0.0399)
Precipitation shock squared×Migrate 1 to 4 years ago	0.0485
	(0.0636)
Precipitation shock squared×Migrate 5 to 9 years ago	-0.0905***
	(0.0322)
Log of imputed wage	0.9951***
	(0.0185)
R-squared	0.59
Observations	2,339
Wald test: All coefficients=0	3708.76***
Wald test: Shock variables=0	13.17***
Wald test: Origin Fixed effects=0	8.55*
Wald test: Destination Fixed effects=0	2.64
Wald test: Origin×Destination Fixed effects=0	29.02**
Wald test: Time Fixed effects=0	8.49

1 Bootstrapped standard errors are in parentheses. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

2 Regional destination fixed effects, regional origin fixed effects, fixed effects interacting regional destination and regional origin dummy variables, and time fixed effects are included in all wage model specifications.

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APPENDIX

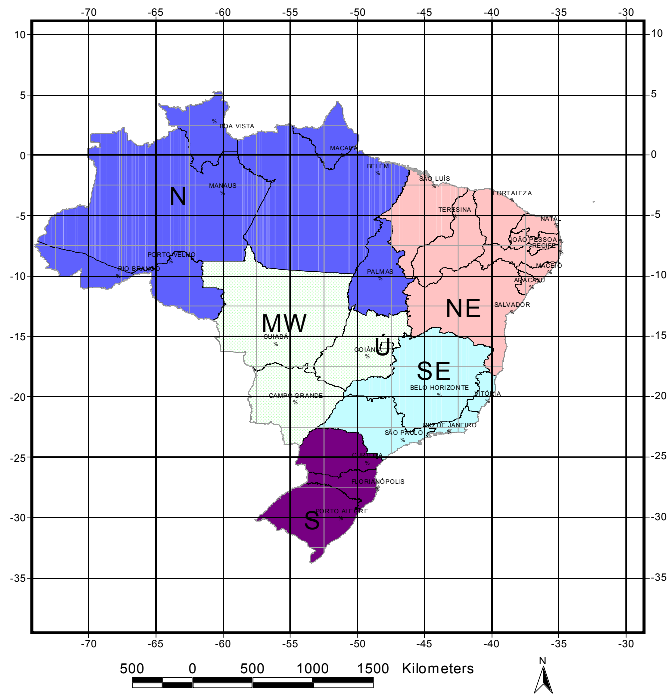

Figure 3: Brazil

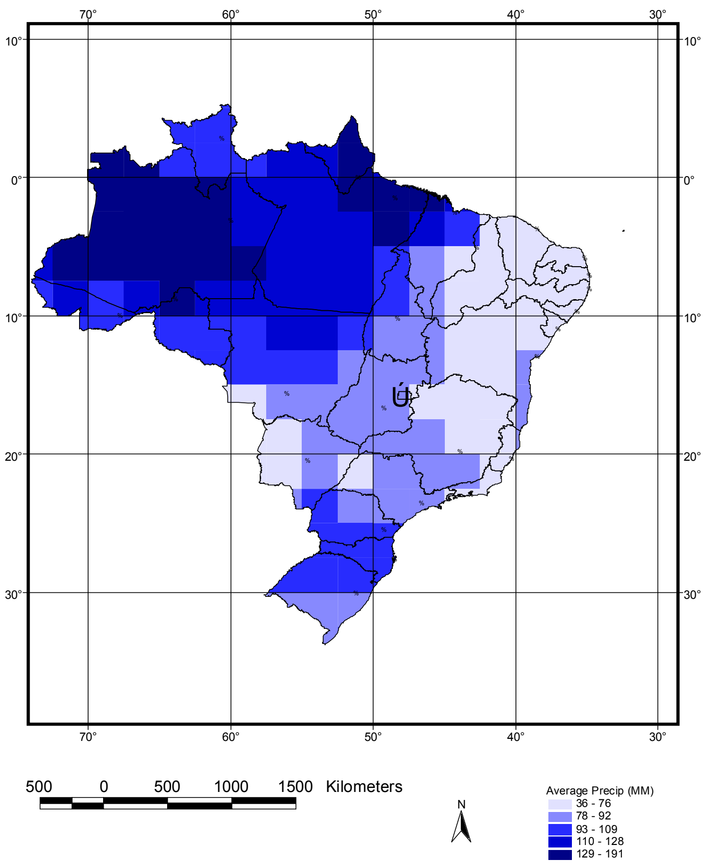

Figure 4: Average Annual Precipitation (Jan 1979-Sep 2004)

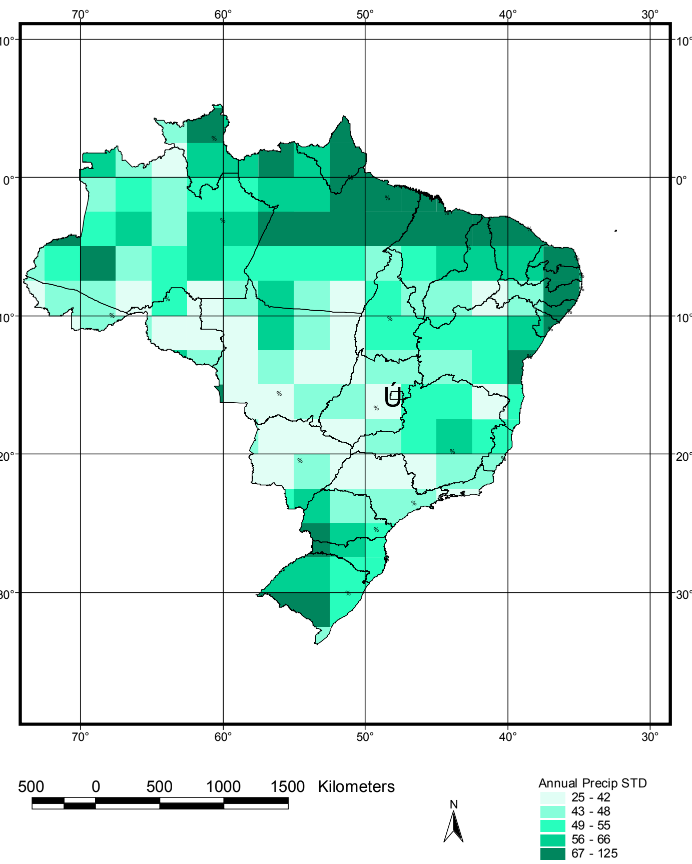

Figure 5: Variation in Annual Precipitation (Jan 1979-Sep 2004)

Table 7: Wage Regression Used to Impute Household Income in Place of Origin

Variable	Parameter	Std.Error (Std. Dev.)
Wage Equation		
Intercept	2.7783	(0.0396)
Male	0.5347	(0.0810)
Black	-0.1484	(0.0762)
Education	0.1201	(0.0151)
Age	0.0768	(0.0136)
Age-squared	-0.0008	(0.0002)
State Fixed Effect	0.1792	(0.2764)
Selection Equation		
Intercept	1.7102	0.0259
Age		
18 to 25	0.8722	0.0143
26 to 40	0.9800	0.0166
41 to 55	0.7875	0.0196
greater than 55	0.3462	0.0247
Male	-0.1772	0.0124
Relationship to Head of Household		
Spouse	-1.2118	0.0178
Child	-0.9824	0.0179
Relative	-0.6536	0.0237
Other	-0.2367	0.0454
Household Size	-0.0242	0.0021
Receipt of Auxiliary Income		
Pension	-0.3024	0.0200
Remittance	-0.5766	0.0617
Dividends	0.3592	0.0387
Region		
North	-0.1825	0.0220
Northeast	-0.5399	0.0126
South	-0.3823	0.0144
Midwest	-0.2883	0.0181
Lambda	-0.3621	0.0075
Sigma	0.7416	0.0020
Rho	-0.4883	0.0095
LR test: Rho=0	1825.67	
LLF	-178837	
Observations	125,190	

Table 8: Household Income Regression with Fixed Effects

Variable	No FE	Origin FE	Origin, Destination FE	Origin, Destination, Origin× Destination FE
Intercept	0.3831***	0.5508***	0.5541***	0.5260***
	(0.1285)	(0.1662)	(0.1635)	(0.1632)
Age	-0.0059***	-0.0059***	-0.0065***	-0.0065***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Precipitation mean	-0.0110	-0.0693**	-0.0658*	-0.0557
	(0.0125)	(0.0346)	(0.0349)	(0.0361)
Precipitation variance	0.1798***	0.2859***	0.2410***	0.2442***
	(0.0709)	(0.0933)	(0.0934)	(0.0940)
Precipitation shock	-0.0280	-0.0279	-0.0249	-0.0278
	(0.0223)	(0.0225)	(0.0225)	(0.0224)
Precipitation shock squared	-0.0615***	-0.0641***	-0.0668***	-0.0695***
	(0.0228)	(0.0227)	(0.0225)	(0.0229)
Log of imputed wage	0.9927***	0.9908***	0.9972***	0.9942***
	(0.0181)	(0.0186)	(0.0187)	(0.0185)
R squared	0.58	0.58	0.58	0.59
Wald test: All coefficients	3169.63***	3229.31***	3306.35***	3528.51***
Wald test: Shock variables	7.40**	8.06**	8.81***	9.28***
Wald test: Origin Fixed effects		3.89	4.52	8.75*
Wald test: Destination Fixed effects			24.90***	2.44
Wald test: Origin×Destination Fixed effects				29.20**

Note: Bootstrapped standard errors are in parentheses. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

Table 9: Additional Specifications of the Household Income Regression

Variable	(I)		(II)		(III)	
Intercept	0.3780**	(0.1684)	0.7956***	(0.1873)	0.5705***	(0.1774)
Number of household members						
aged 11 to 17			0.0062	(0.0158)		
aged 18 to 25			0.0318*	(0.0171)		
aged 26 to 40			-0.0129	(0.0216)		
aged 41 to 64			-0.0584**	(0.0247)		
aged greater than 64			-0.1929***	(0.0458)		
Education						
5 to 8 years			-0.0176	(0.0333)		
9 to 12 years			-0.0407	(0.0415)		
greater than 12 years			0.3546***	(0.0603)		
Age					-0.0066***	(0.0012)
Distance					-0.0076	(0.0090)
Distance squared					0.0002	(0.0003)
Precipitation mean	-0.0628*	(0.0353)	-0.0480	(0.0348)	-0.0553	(0.0362)
Precipitation variance	0.2504***	(0.0955)	0.2590***	(0.0929)	0.2548***	(0.1005)
Precipitation shock	-0.0019	(0.0279)	-0.0029	(0.0270)	-0.0015	(0.0276)
Precipitation shock squared	-0.0647***	(0.0252)	-0.0638***	(0.0249)	-0.0670***	(0.0253)
Log of imputed wage	0.9820***	(0.0185)	0.9098***	(0.0268)	0.9963***	(0.0186)
R squared	0.58		0.60		0.59	
Wald test: All coefficients	3610.99***		3932.25***		3668.62***	
Wald test: Shock variables	7.13**		7.12**		7.78**	
Wald test: Distance variables					0.71	

1 Bootstrapped standard errors are in parentheses beside the parameter estimates. ***, **, and * indicate the parameters are significant at the 1, 5, and 10 percent critical levels.

2 The distance variable is divided by 100.

3 Regional destination fixed effects, regional origin fixed effects, fixed effects interacting regional destination and regional origin dummy variables, and time fixed effects are included in all wage model specifications.

4 Model I excludes household variables. Model II adds to Model I the number of household members by age category variables and head of household's education variables. Model III adds to Model I the head of household's age and the distance variables.