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Temporary Migration and Endogenous Risk Sharing in Village India

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Abstract

When people can self-insure via migration, they may have less need for informal risk sharing. At the same time, informal insurance may reduce the need to migrate. To understand the joint determination of migration and risk sharing I study a dynamic model of risk sharing with limited commitment frictions and endogenous temporary migration. First, I characterize the model. I demonstrate theoretically how migration may decrease risk sharing. I decompose the welfare effect of migration into the change in income and the change in the endogenous structure of insurance. I then show how risk sharing alters the returns to migration. Second, I structurally estimate the model using the new (2001-2004) ICRISAT panel from rural India. The estimation yields: (1) improving access to risk sharing reduces migration by 21 percentage points; (2) reducing the cost of migration reduces risk sharing by 8 percentage points; (3) contrasting endogenous to exogenous risk sharing, the consumption-equivalent gain from reducing migration costs is 18.9 percentage points lower. Third, I introduce a rural employment scheme. The policy reduces migration and decreases risk sharing. The welfare gain of the policy is 55-70% lower after household risk sharing and migration responses are considered.

Keywords: Internal migration, Risk Sharing, Limited Commitment, Dynamic Contracts, India, Urban, Rural
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1 Introduction

Rural households in developing countries face extremely high year-to-year volatility in income. Economists have long studied the complex systems of informal transfers that allow households to insulate themselves against income shocks in the absence of formal markets (Udry, 1994; Townsend, 1994). However, households can also migrate temporarily when hit by a bad economic shock. In rural India, 20% of households have at least one temporary migrant, with migration income representing 50% of total income for these households. The possibility of migration offers a form of self-insurance, hence may fundamentally change the incentives for households of participating in informal risk sharing. At the same time, informal risk sharing provides insurance against income shocks, altering the returns to migrating. In order to appropriately understand the benefits of migration, and to think about policies to help households address income risk, it is therefore important to consider the joint determination of risk sharing and migration.

To analyze this interaction between risk sharing and migration I study a dynamic model of risk sharing that incorporates limited commitment frictions and endogenous temporary migration. Households take risk sharing into account when deciding to migrate. Similarly, the option to migrate affects participation in informal risk sharing. My model combines migration due to income differentials (Sjaastad, 1962; Harris and Todaro, 1970), and risk sharing with limited commitment frictions (Kocherlakota, 1996; Ligon, Thomas and Worrall, 2002). First, I characterize the model and develop comprehensive comparative statics with respect to migration, risk sharing and welfare. I demonstrate theoretically the channels through which migration may decrease risk sharing, by changing the value of the outside option for households. I decompose the welfare effect of migration into the change in income and the change in the endogenous structure of the insurance market. I then show how risk sharing alters the returns to migration and determines the migration decision. Second, I apply the model to the empirical setting of rural India. I structurally estimate the model using the second wave of the ICRISAT household panel dataset (2001-2004). The quantitative results are as follows: (1) introducing migration into the model reduces risk sharing by 8 percentage points%; (2) contrasting endogenous to exogenous risk sharing, the consumption-equivalent gain in welfare from introducing migration is 18.9 percentage points lower; (3) improving access to risk sharing reduces migration by 21 percentage points. Third, I show that the joint determination of risk sharing and migration of the household may have key policy implications. I simulate a rural employment scheme (similar to the Indian Government's National Rural Employment Guarantee Act) in the model. Households respond to the policy by adjusting both migration and risk sharing: migration decreases and risk sharing is reduced. I show the welfare benefits of this policy are overstated if the joint responses of migration and risk sharing are not taken into account. The welfare gain of the policy is 55-70% lower after household risk sharing and migration responses are considered.

A key focus is the analysis of temporary migration. Because migration is temporary, households remain part of the risk sharing network if they migrate. This differs to the case of permanent migration, where households permanently leave the village and exit the risk sharing network if they migrate (Banerjee and Newman, 1998; Munshi and Rosenzweig, 2015). Temporary migration is the relevant migration margin to focus on for the case of rural India because permanent migration is very low (Munshi and Rosenzweig, 2015; Topalova, 2010), but, as I document in this paper, temporary migration is widespread. Because migrants remain in the risk sharing network, a key contribution of this paper is to quantify how the risk sharing network adjusts to migration. As a result, the model predicts that migration will affect the entire network, not only those households who migrate, and analyzing the effect of migration on these households is important to understand the full impact of migration.

Another important contribution of the paper is the joint determination of migration and risk sharing. Empirical tests reject the benchmark of perfect insurance, but find evidence of substantial smoothing of income shocks (Mace, 1991; Altonji, Hayashi and Kotlikoff, 1992; Townsend, 1994; Udry, 1994). Models of limited commitment endogenously generate incomplete insurance because insurance is constrained by the fact that households can walk away from any agreement (Kocherlakota, 1996; Ligon, Thomas and Worrall, 2002; Alvarez and Jermann, 2000).[1] Using the limited commitment framework,

[1]See also the application of limited commitment in labor markets (Harris and Holmstrom, 1982; Thomas

other studies have examined how endogenous risk sharing responds to changes in households' outside option, including public insurance schemes (Attanasio and Rios-Rull, 2000; Albarran and Attanasio, 2003; Golosov and Tsyvinski, 2007; Abramitzky, 2008; Krueger and Perri, 2010), unemployment insurance (Thomas and Worrall, 2007), and options to save (Ligon, Thomas and Worrall, 2000). However, these papers have not examined how migration decisions are codetermined with risk sharing decisions.

On the migration side, in a standard migration model households take into account income differentials between the village and city and migrate if the utility gain of doing so is positive (Lewis, 1954; Sjaastad, 1962; Harris and Todaro, 1970). In contrast, when households are part of a risk sharing agreement, the relevant comparison is post-transfer, rather than gross, income differentials. As a result, risk sharing has two effects on migration. In the model, households use migration as an ex post income smoothing mechanism, so those who migrate are the households who have bad income shocks. These households would be net recipients of risk sharing transfers in the village. Risk sharing reduces the income gain between the village and city and decreases migration. On the other hand, migration is risky (Bryan, Chowdhury and Mobarak, 2014; Tunali, 2000). Risk sharing can insure the risky migration outcome, facilitating migration. The paper also fits into a broader literature examining the determinants and benefits of migration and remittances[2]; I add to this literature by showing that to fully appraise the benefits and costs of migration it is important to study how migration interacts with informal risk sharing.

Before proceeding to the structural estimation, I first establish five empirical facts relating migration to risk sharing. First, migration responds to exogenous income shocks. When the monsoon rainfall is low, migration rates are higher. This matches the mod-

and Worrall, 1988) and insurance markets (Hendel and Lizzeri, 2003).

[2]For example, In India Rosenzweig and Stark (1989) show that marriage-migration can be an important income smoothing mechanism for households. Yang and Choi (2007) show that remittances from migrants respond to income shocks. In a series of papers looking at rural-urban migration in China, Giles (2006, 2007); de Brauw and Giles (2014) show migration acts to reduce the riskiness of household income in the destination, reduce precautionary savings, and potentially shift production into more risky activities. Bryan et al. (2014) document large returns to migration in a randomized controlled trial in Bangladesh. Other studies have investigated the role of learning in explaining observed migration behavior, particularly repeat migration (Pessino (1991); Kennan (2013)).

eling assumption that migration decisions are made after income is realized. Second, households move in and out of migration status. 40% of households migrate at least once during the sample. However, on average, a migrant household only migrates half the time. This is consistent with households migrating in response to income shocks, rather than migration being a permanent strategy. Third, risk sharing is imperfect, and is worse in villages where temporary migration is more common. This is consistent with an interaction between informal risk sharing and migration. Fourth, conditional on income, the past history of transfer negatively predicts current transfers. This is consistent with the limited commitment model (Foster and Rosenzweig, 2001). Fifth, although a household increases their income by 30% during the years they send a migrant, total expenditure (consumption and change in asset position) only increases by 85% of the increase in income. This last fact is consistent with the migrant making transfers back to the network.

To quantify the effects of the joint determination of migration and risk sharing I structurally estimate the model. Empirically, households are more likely to migrate if they have more males and if they have lower landholdings. To match this observed heterogeneity in migration across households, I allow for heterogeneity in land holdings to affect village income and for households to face different costs of migration depending on their household composition (in particular, the number of males in the household).[3] Using the structural estimates I then construct quantitative counterfactuals to simulate the effects of reducing the costs of migration on risk sharing, the costs of increasing access to risk sharing on migration, and illustrate how the joint determination of migration and risk sharing has key implications for understanding benefits of policies designed to address the income risk faced by poor rural households, using the example of the Indian Government's National Rural Employment Guarantee Act.

In the following section, I present the risk sharing model with endogenous migration. Section 3 introduces the household panel used to estimate the model, and verifies that the modeling assumptions hold in these data. Section 4 discusses how to apply the model to

[3] In Section 3 I discuss an alternative hypothesis that the reason males migrate more than females is because of higher returns, rather than lower costs. However, using labor market data, I find, if anything, evidence of higher returns to migration for females than males (although the number of females migrants is small). For this reason I model that differential costs of migration is driving the heterogeneity in migration rates.

the data, and Section 5 presents the structural estimation results and performs the policy experiments. Section 6 concludes with a discussion of the findings.

2 Joint model of migration and risk sharing

Consider a two household endowment economy. All households have identical preferences.[4] In each period t the village experiences one of finitely many events s_t that follows a Markov process with transition probabilities $\pi^s(s_t|s_{t-1})$. The village event determines the endowment of each household in the village, $e^i(s_t)$. Denote by $s^t = (s_0, ..., s_t)$ the history of events up to and including period t. The probability, as of period 0, of any particular history s^t is $\pi^s(s^t|s_0) = \pi^s(s_t|s_{t-1})...\pi^s(s_1|s_0)$. For shorthand, denote $\pi^s(r|s) = \pi(s_{t+1} = r|s_t = s)$. Households cannot borrow or save in autarky. Including savings would introduce an additional state variable into the maximization problem. In the data, I find that savings (including in both financial and physical assets such as livestock) are small and importantly do not respond to migration. I therefore abstract from capital accumulation to highlight the main mechanism of interest, the interaction between migration and risk sharing.[5]

Temporary migration is the choice to migrate away from the village for one period. Migration is modeled at the household level, abstracting from within household issues. This assumption implies that within-household risk sharing is Pareto efficient.[6] I do not explicitly model which household member migrates. However, I allow overall household composition to matter for potentially affect the migration decision at the household level: for example, households who have more land may have higher opportunity costs of migrating, and households who have more males may face differential access to migration opportunities. Household characteristics will be indexed by a vector z^i; where z contains the characteristics of all households in the village.[7]

[4]For papers that analyze risk sharing when preferences are heterogeneous, see Mazzocco and Saini (2012); Chiappori, Samphantharak, Schulhofer-Wohl and Townsend (2014) and Schulhofer-Wohl (2011).

[5]For papers that extend limited commitment to include asset accumulation, see for example Ligon et al. (2000); Kehoe and Perri (2002); Krueger and Perri (2006); Abraham and Laczo (2014).

[6]For studies examining migration with intra-household incentive constraints, see Chen (2006); Gemici (2011); Dustmann and Mestres (2010).

[7]The abstraction of which member migrates is for two reasons. First, in the data, there does not appear

In period t the migration destination experiences also one of finitely many events q_t. The destination event determines the migration income for household i if they migrate, $m^i(q_t)$. Assume that the probability of migration event q_t is independent of the village event, and is independent across time, $\pi^q(q_t = q) = \pi^q(q), \forall t$.[8]

Let $\mathbb{I}^i$ be an indicator variable for whether household i migrates. Each household either sends or does not send a migrant so there are 4 possible migration outcomes, indexed by j. Denote the migration status of household 1 and 2 by the vector $\mathbb{I}(j) = \{\mathbb{I}^1(j), \mathbb{I}^2(j)\}$.

The timing in the model is as follows. Households observe their endowment in the village (state s) and decide whether to send a temporary migrant to the city. If a household sends out a migrant they then realize their migration income (state q) and pay a utility cost $d(z_i)$, which captures both the physical costs (for example, costs of transportation) and the psychic costs (for example, being away from friends and family) of migration (Sjaastad, 1962).[9] This timing assumption is based on two empirical facts which are documented in Section 3. First, the average migration rate depends on the rainfall realization, consistent with households making migration decisions after observing the village level income. Second, many migrants in the data experience unemployment in the destination, consistent with migration income not being realized until after the migration decision occurs.[10]

to be a large role for comparative advantage in migration inside the household: there are very small returns to observable characteristics such as education, age, gender and experience in the destination labor market (results available upon request). Second, within household, which members(s) migrate is highly correlated over time: in 77% of households exactly the same members migrated together any time any one member migrated, consistent with the choice of migrants being constant within household over time.

[8]This assumption is also supported empirically: in contrast to other studies such as Bryan et al. (2014), I find no evidence of returns to migration experience.

[9]It is reasonable to think about whether households may have heterogeneous migration costs, such as in Kennan and Walker (2011). A household who receives a low cost shock (e.g. a discounted bus ticket) may be more likely to migrate conditional on the income realization. This introduces a difference between the ex-ante average migration cost for a household in the village, and the realized migration cost for those who choose to migrate. While I don't explicitly model this, there is a mapping between preference shocks and the estimation method I employ. If households had type 1 extreme value preference shocks then the migration decision takes the form $\pi_{\text{migrate}} = \frac{\exp(V_{\text{mig}})}{\exp(V_{\text{mig}})+\exp(V_{\text{no mig}})}$. When I estimate the model I employ a smoothing estimator to approximate the discrete function (following the methodology in Horowitz (1992); Keane and Smith (2004)). The probability of migration with this estimator is given by $\pi_{\text{migrate}} = \frac{\exp(V_{\text{mig}}/\lambda)}{\exp(V_{\text{mig}}/\lambda)+\exp(V_{\text{no mig}}/\lambda)}$ (which approximates the discrete case as $\lambda \to 0$). Hence, the estimated migration cost parameter can be interpreted as the expected ex-ante migration cost faced by households in the village.

[10]The magnitudes are the following. (i) A realization of rainfall one standard deviation about the mean

For state of the world s_t and migration outcome q_t, ex-post income for household i is given by $y^i(s_t, q_t, j_t; z^i) = \mathbb{I}^i(j_t)m^i(q_t) + (1 - \mathbb{I}^i(j_t))e^i(s_t)$. Once all income is realized, households make or receive risk sharing transfers, and consumption occurs. At the end of the period the migrant returns back to the village. The same problem is faced the following period.

2.1 Model of endogenous migration and risk sharing

First, I present the model of migration and risk sharing under full commitment. Following the setup in Ligon et al. (2002), the social planner maximizes the utility of household 2, given a state dependent level of promised utility, $U(s)$, for household 1.

The optimization problem is to choose migration, transfers, and continuation utility to maximize total utility:

$$V(U(s); z) = \max_j \sum_j \tilde{V}(U(s), j; z)$$

where $\tilde{V}(U(s), j; z)$ is the expected value if migration decision j is chosen:

$$\tilde{V}(U(s), j; z) = \max_{\tau(q,j), \{U'(q,j,r;z)\}_{r=1}^R} \mathrm{E}_q \left[u(\tilde{y}^2(s, q, j) + \tau(q, j)) - \mathbb{I}^2(j)d(z^2) + \beta \sum_r \pi^s(r|s) V(U'(q, j, r; z)) \right]$$

subject to a promise keeping constraint that expected utility is equal to promised utility:

$$\mathrm{E}_q \left[u(\tilde{y}^1(s, q, j; z) - \tau(q, j)) - \mathbb{I}^1(j)d(z^1) + \beta \sum_r \pi^s(r|s) U'(q, j, r; z) \right] = U(s; z) \ \forall j$$

Let λ be the multiplier on the promise keeping constraint. The first order condition yields the familiar condition that the ratio of marginal utilities of consumption are equal-

reduces village level migration by 3.6 percentage points. (ii) 37% of migrants report some involuntary unemployment. Across all migrants the mean is 11 days out of an average trip length of 180 days; conditional on reporting some unemployment, the mean is 31 days out of an average trip length of 192 days. See Section 3 for a full discussion.

ized across all states of the world and migration states:[11]

$$\frac{u'(c^2(s,q,j;z))}{u'(c^1(s,q,j;z))} = \lambda \quad \forall s,q,j$$

2.2 Adding in limited commitment

Now introduce limited commitment constraints into the model. The key mechanism in the limited commitment model is the value of walking away and consuming the endowment stream (the "outside option") (Kocherlakota, 1996; Ligon, Thomas and Worrall, 2002).[12] In a world where agents can migrate, compared to a world where they cannot migrate, the opportunity to migrate weakly increases the outside option of households and will endogenously affect the amount of insurance that can be sustained.

I study the constrained efficient joint decision of migration and risk sharing. That is, a social planner chooses both migration and risk sharing transfers to maximize total utility, conditional on satisfying two incentive compatibility constraints. These two constraints correspond to the two potential times in which a household may wish to renege. The first is at the time that migration decisions are made: the ex ante (before migration occurs) expected value of following the social planner's migration rule (and continuing to participate in the risk sharing network) needs to be at least as large as the ex ante expected value of making an independent migration decision and then being in autarky. The second is after migration decisions have been made and all migration outcomes have been realized. At this stage the final income has been realized and the ex post (after migration has occured) value of following the social planner's risk sharing transfer rule needs to be at least as high as the ex post value of consuming this current income and then remaining in autarky. This first incentive compatibility constrain is a new constraint I introduce to capture the constrained efficient migration decision. The second constraint is similar to the standard limited commitment constraint (such as in Kocherlakota (1996); Ligon et al.

[11] These first order conditions only hold for interior solutions i.e. the the migration state that occurs with positive probability. When I estimate the model I smooth the discrete objective function; doing so implies that there is an interior solution for all j.

[12] See also Coate and Ravallion (1993); Kehoe and Levine (1993); Attanasio and Rios-Rull (2000); Dubois, Jullien and Magnac (2008).

(2002)): the incentive to remain in the network after income uncertainty has been realized depends on the realization of that income.

To be precise, define the outside option at the two key points in time as follows. Ex-ante autarky, Ω, is the value of deciding whether or not to migrate today, only knowing the state of the world in the village (s), and then facing the same choice in the future:

$$\Omega^i(s;z^i) = \max\{u(y^i(s)); \mathrm{E}_q[u(m^i(q)) - d(z^i)]\} + \beta \sum_r \pi^s(r|s)\Omega^i(r;z^i)$$

Ex-post autarky, $\tilde{\Omega}$, is the value of consuming period t income, conditional on the migration choice (j), the state in the village (s) and the state in the destination (q), and then facing the ex-ante decision problem from period $t+1$.

$$\tilde{\Omega}^i(s,q,j;z^i) = u(\tilde{y}^i(s,q,j;z)) - \mathbb{I}^i(j)d(z^i) + \beta \sum_r \pi^s(r|s)\Omega^i(r;z^i)$$

The first set of incentive compatibility constraints are ex ante constraints that require that the expected gain of participating in the risk sharing migration will be higher than the expected value of being independent. These are:

$$\begin{aligned}
(\beta\pi^s(r|s)\pi(q)\phi^1_{q,j,r}): &\quad U'(q,j,r;z) - \Omega^1(r;z^1) \geq 0 \quad \forall q,j,r \\
(\beta\pi^s(r|s)\pi(q)\phi^2_{q,j,r}): &\quad V(U'(q,j,r;z);z) - \Omega^2(r;z^2) \geq 0 \quad \forall q,j,r
\end{aligned}$$

The second set of constraints, the ex post constraints (satisfied once migration decisions are made and income realized), require that the current utility is at least as high as the value of being in autarky:

$$\begin{aligned}
(\pi(q)\alpha^1(q,j)): &\quad u(\tilde{y}^1(s,q,j) - \tau(q,j)) - \mathbb{I}^1(j)d(z^1) + \beta \sum_r \pi^s(r|s)U'(q,j,r;z) - \tilde{\Omega}^1(s,q,j;z^1) \geq 0 \quad \forall s,q,j \\
(\pi(q)\alpha^2(q,j)): &\quad u(\tilde{y}^2(s,q,j) + \tau(q,j)) - \mathbb{I}^2(j)d(z^1) + \beta \sum_r \pi^s(r|s)V(U'(q,j,r;z);z) - \tilde{\Omega}^2(s,q,j;z^2) \geq 0 \quad \forall s,q,j
\end{aligned}$$

It is convenient to rescale the multipliers for person 1 by their initial weight, λ. Then, the first order conditions and envelope condition can be written as:

$$\frac{u'(c^2(s,q,j;z))}{u'(c^1(s,q,j;z))} = \lambda \frac{1+\alpha^1(q,j)}{1+\alpha^2(qj)} \quad \forall s,q,j$$

$$V'(U(q,j,r;z);z) = -\lambda \frac{1+\alpha^1(q,j)+\phi^1(q,j,r)}{1+\alpha^2(q,j)+\phi^2(q,j,r)} \quad \forall s,q,r,j$$

$$V'(U(s);z) = -\lambda$$

where the marginal utility is updated to take into account the outcome of uncertain migration outcomes. The slope of the value function is updated depending on both the ex-ante and the ex-post constraints:

$$V'(U(q,j,r;z);z) = V'(U(s);z)\frac{1+\alpha^1(q,j)+\phi^1(q,j,r)}{1+\alpha^2(q,j)+\phi^2(q,j,r)} \quad \forall s,q,r,j$$

2.3 Comparative statics on migration, risk sharing, and welfare

This section derives results on migration, risk sharing and welfare.

2.3.1 Effect of improving access to risk sharing on migration

How does introducing access to risk sharing, compared to a world in which risk sharing is not possible, affect migration decisions?[13]

Under autarky, households compare the rural-urban wage differential, and migrate if expected utility gain is positive. Under risk sharing, households compare the post-transfer rural-urban income differentials instead of comparing the gross income differentials. Improving access to risk sharing will have two offsetting effects on migration. Households who migrate are the households who have bad income shocks. These households would be net recipients of risk sharing transfers in the village. Facilitating risk sharing reduces the income gain between the village and city and decreases migration

[13] For example, assume that there is an exogenous per-unit cost, d_τ to transfer resources between households, such that \$1 sent from household yields \$$(1-d_\tau)$ for the recipient household. Introducing risk sharing can be modeled as a reduction in this cost of transferring resources. In the extreme, when $d_\tau = 1$ households will never find it optimal to make risk sharing transfers. When $d_\tau = 0$ risk sharing transfers are costless.

(the 'home' effect). On the other hand, migration is risky. Risk sharing can insure the risky migration outcome, facilitating migration (the 'destination' effect). The net effect of improving risk sharing (by reducing the cost of inter-household transfers) on migration will depend on whether the destination effect is larger than the home effect.

2.3.2 The effect of reducing the cost of migration on risk sharing

The decision to migrate depends on the cost of migrating, d. Consider a reduction in the cost of migrating. How does this affect risk sharing?

Reducing the costs of migration may affect both the distribution of consumption and the distribution of income across households in the village. Define risk-sharing, following Krueger and Perri (2010), as the ratio of the variance of consumption, σ^c, to the variance of ex-post income, σ^y. Both of these variances are endogenous objects and will depend on the distribution of earnings in the village, F_E, the distribution of earnings in the destination, F_M, the cost of migration, d, and the cost of transferring resources between households, d_τ.

Definition 1. *Risk sharing* is defined as $RS_t = 1 - \frac{\sigma^c(F_E, F_M, F_E, d, d_\tau)}{\sigma^y(F_E, F_M, F_C, d, d_\tau)}$ where σ^c is the standard deviation of consumption and σ^y is the standard deviation of realized (ex-post of any migration) income.

This measure of risk sharing is bounded between 0 and 1, taking the value 1 if resources are perfectly shared between households ($\sigma^c = 0$) and the value 0 if there is no transfer of resources ($\sigma^c = \sigma^y$). The net effect of reducing the cost of migration on risk sharing will depend on how reducing the cost of migration affects the distribution of consumption relative to how it affects the distribution of income.

Using the chain rule, decompose the change in risk sharing from an exogenous reduction in the cost of migrating, d, as:

$$\frac{\mathrm{d}RS_t}{\mathrm{d}d} = \underbrace{\frac{\partial RS_t}{\partial \sigma^c}\left(\frac{\partial \sigma^c(F_E, F_M, d, d_\tau)}{\partial d}\right)}_{\text{Consumption effect}} + \underbrace{\frac{\partial RS_t}{\partial \sigma^y}\left(\frac{\partial \sigma^y(F_E, F_M, d, d_\tau)}{\partial d}\right)}_{\text{Income effect}}$$

The consumption effect represents the change in the standard deviation of consumption as a result of the reduction in migration costs. The standard deviation of consumption could change because of a change in the distribution of income, which will then affect transfers and hence consumption. It could also change because the reduction in migration costs changes the outside option of households, which changes the incentives for households to participate in risk sharing. For example, if it were the case that the reduction in migration costs made autarky more attractive it may reduce the amount of risk sharing transfers households make and increase the variance of consumption. This could occur even if no households choose to exercise the option to migrate in which case the standard deviation of income would be unchanged and so risk sharing would reduce. On the other hand, if reducing the cost of migrating allowed households to migrate out in times of bad aggregate shocks, this may make it easier to make transfers between households because households have more income and hence lower marginal utilities (making participation constraints easier to satisfy). This could reduce the distribution of consumption as well as affecting the distribution of income and the net effect on risk sharing would depend on the relative magnitude of the two effects.

2.3.3 Decomposition of the welfare effect of reducing the cost of migration

Total welfare depends on the distribution of consumption and total income. Total welfare is maximized if all households have an equal share of consumption (if $\sigma^c = 0$). I approximate welfare for this economy as a function of the distribution of consumption (σ^c) and moments summarizing the distribution of expost income F_Y:[14]

$$W = W(\sigma^c(F_E, F_M, d_\tau, d), \mu_Y(F_E, F_M, d_\tau, d))$$

Reducing migration costs will have two effects on welfare. First, it directly changes the total resources available to the network. Second, it endogenously changes the distribution of consumption among network members. Decompose the change in welfare into the

[14] I use a first order approximation for the effect of the income distribution on welfare. Higher order moments of the income distribution may also be important for welfare and could easily be incorporated into this formula.

change in risk sharing (summarized by σ^c) and the change in the income distribution μ_Y:

$$\frac{\mathrm{d}W}{\mathrm{d}d} = \underbrace{\frac{\partial W}{\partial \sigma^c}\frac{\partial \sigma^c(F_E, F_M, d_\tau, d)}{\partial d}}_{\text{Risk sharing effect}} + \underbrace{\frac{\partial W}{\partial \mu_Y}\frac{\partial \mu_Y(F_E, F_M, d_\tau, d)}{\partial d}}_{\text{Income effect}}$$

The risk sharing effect captures how the distribution of consumption changes. Total welfare is maximized when the cross-sectional distribution of consumption is zero, and welfare is lower when risk sharing is reduced. As a result, $\frac{\partial W}{\partial \sigma^c}$ is negative. The sign of the first term will therefore depend on the effect of reducing the cost of migrating on risk sharing. The income effect captures the change in income as a result in the reduction cost of migration. It is positive: higher income increases welfare. The net effect on welfare from reducing the costs of migration depends on the relative magnitude of the income and risk-sharing effects. A priori, the net welfare effect of migration can be either positive or negative.

2.4 Summary of theoretical predictions

This section presents a model of limited commitment with endogenous temporary migration where migration and risk sharing were jointly determined. I derive three comparative statics:

1. *Effect of reducing the cost of migration on risk sharing:* Reducing the cost of migration will change both the distribution of income and the endogenous distribution of consumption. If the variance of consumption decreases relative to the variance of income, then risk sharing increases. Theoretically, the effect of migration on risk sharing is ambiguous. On one hand, the option to migrate increases the outside option of households, decreasing risk sharing. On the other hand, migration allows the network to act to smooth aggregate shocks, increasing risk sharing.

2. *Decomposition of the welfare effect of reducing the cost of migration:* Welfare depends on total resources available to the network and the allocation of these resources between members (the "size" and "slices" of the economic pie). The effect of reducing

the cost of migration on welfare can be decomposed into an income effect and a risk sharing effect. In the first case, changing the income distribution while holding the allocation constant has a positive effect on welfare. At the same time, reducing the costs of migration affects the outside option of households, which may make it more difficult to satisfy incentive compatibility constraints and reduce the amount of risk sharing, in turn reducing welfare.

3. *Effect of reducing the cost of interhousehold transfers on migration:* In the presence of any risk sharing, the migration decision depends on post-transfer income differentials between the village and city. There is a destination effect and a home effect. Households who migrate are the households who have bad income shocks. These households would be net recipients of risk sharing transfers in the village. Reducing the cost of interhousehold transfers improves risk sharing and reduces the income gain between the village and city and decreases migration. On the other hand, migration is risky. Improving risk sharing by reducing the cost of transfers can insure the risky migration outcome, facilitating migration.

Because the theoretical results are ambiguous, determining the net effect is an empirical question. I now introduce the empirical setting of rural India, where I will estimate the model.

3 Panel of rural Indian households

This paper uses the new ICRISAT data (VLS2) collected between 2001-2004 from semi-arid India. The ICRISAT data are a very detailed panel household survey, with modules covering consumption, income, assets, and migration.[15]

[15] The VLS2 data can be merged onto the original first wave (VLS1) ICRISAT data, covering 1975-1984. Pooling the two waves yields a 30-year panel on rural households. While it would be interesting to study the long run development of village economics between 1975 and 2004, the focus of the current paper is on the joint determination of migration and risk sharing. For this reason, I focus on the second wave of the data where both mechanisms are present.

3.1 Descriptive statistics of migration

Because of its short term nature, temporary migration is often undercounted in standard household surveys. A key feature of the ICRISAT data is the presence of a specific module on temporary migration. Such a module was included because temporary migration is widespread: in the ICRISAT data, 20% of households participate in temporary migration each year. The prevalence of temporary migration varies over location, village and time. For example, migration is much higher in the two villages in the state of Andhra Pradesh due to their proximity to Hyderabad, a main migration destination. Figure 1 plots migration prevalence by village and year.

It is reassuring to check that migration behavior observed in the ICRISAT villages is consistent with other studies. Other household surveys in India find widespread temporary migration of up to 50% (Rogaly and Rafique, 2003; Banerjee and Duflo, 2007). Coffey et al. (2014) survey households in a high-migration area in North India and find that 82% of households had send a migrant in the last year. The nationally representative National Sample Survey (NSS) asks about short term migration, defining it as trips between 30-180 days. However, there is evidence that the NSS may undercount shorter-term migration episodes. Imbert and Papp (2015b) use NSS data and find national short term migration rates of 2.5%; for the specific regions that overlap with the household survey in Coffey et al. (2014) the short-term migration rate in the NSS data is 16%, compared with 30% in the household survey. Taken together, these studies suggest that the migration rates observed in the ICRISAT data, of approximately 20%, are consistent with other data from India and Bangladesh.[16]

Summary statistics for the sample are reported in Table 1. On average, a migration trip lasts for 193 days (approximately six months) and 1.8 members of the household migrate. 40% of households have a migrant at least one of the four years of the survey. Migrants are predominantly men: only 28% of temporary migrants are women. However, these women are almost always accompanied by a male member of the household. If there is

[16] For prevalence of temporary migration in other developing countries refer to de Brauw and Harigaya (2007) (Vietnam); Macours and Vakis (2010) (Nicaragua); Bryan, Chowdhury and Mobarak (2014) (Bangladesh).

only one migrant from a household, 94% of the time this is a male migrant.

Households who ever migrate are different than households who never migrate. Migrating households have a slightly larger household, more adult males (2.2 vs 1.7), and less land (4.5 vs 5.1 acres). A probability model for ever migrating is reported in Appendix Table 1. The number of males, controlling for household size, positively predicts migration. The interaction between males and land owned negatively predicts migration. This appears reasonable: households with more land have higher income in the village and so lower returns to migrating, and households with more males may have surplus labor and hence more likely to migrate.

What is the source of the heavily skewed male migration? One hypothesis is that males have higher returns to migrating than females. Another explanation could be that there are differential costs to migrating, and women have higher migration costs.[17] To examine this I look at the individual labor market data to examine the differential returns to observable characteristics for men and women. This is reported in Appendix Table 2. While males have higher returns in the destination labor market (22 log points), they in fact have differentially lower returns to migrating than women because the male wage premium in the village is 69 log points. The returns to education are higher in the destination for women than for men (10.8% vs 3.4%). However, the level of education does not predict female migration (coefficient of 0.0). Taken together, this suggests that, if anything, women have higher relative returns to migrating than men, so lower returns shouldn't be the explanation for lower rates of female migration. Given this, I make the assumption that returns to migration are homogenous across individuals,[18] but males (and households with more males) face lower costs of migrating. These differential costs of migrating will be the reason that households with more males have higher migration

[17] For example, one reason migration costs may be higher for women than for men could be due to migration being unsafe. In a survey of temporary migrants Coffey et al. (2014) found that 85% of migrants had no formal shelter in the destination. It is easy to imagine that this environment could be more unsafe for women than for men.

[18] With richer data on outcomes this assumption could plausibly be relaxed and heterogenous specific migration returns could be calculated, at a substantial increase in the computational burden of the problem. However, since I find little evidence to differential returns on observable characteristics or migration experience (results in Appendix Table 2) this does not seem to be a key component to understand the temporary migration decision and so I focus on the key mechanism studied in this paper, namely the interaction between migration and risk sharing.

rates than households with fewer males.

3.2 Five key facts linking migration and risk sharing

I verify five key facts in the data: (1) migration responds to exogenous income shocks; (2) households move in and out of migration status; (3) risk sharing is imperfect, and is worse in villages where temporary migration is more common; (4) risk sharing transfers depend negatively on the history of past transfers; and (5) the marginal propensity to consume from migration income is less than 1. Throughout the rest of the analysis I scale all household variables to per adult equivalents, to control for household composition. I define household composition based on the first year in the survey to control for endogenous changes due to migration.

1. *Migration responds to exogenous income shocks*

   The summer monsoon rain at the start of the cropping season is a strong predictor of crop income (Rosenzweig and Binswanger, 1993). I verify the result of Badiani and Safir (2009) and show, in Figure 2, that migration responds to aggregate rainfall. When the monsoon rainfall is low, migration rates are higher.[19] This matches the modeling assumption that migration decisions are made after income is realized.

2. *Households move in and out of migration status*

   40% of households migrate at least once during the sample period. However, on average, a migrant household only migrates half the time. This is consistent with households migrating when their returns are highest – for example, if they receive a low idiosyncratic shock – rather than migration being a permanent strategy.

3. *Risk sharing is incomplete*

   Risk sharing in the ICRISAT villages is incomplete, and worse in villages with

[19] Pooling across villages, the coefficient on the standardized June rainfall is -0.036 without village fixed effects, or -0.024 with village fixed effects; in both cases the constant in the regression is 0.18. Migration caused by ex-post response to rainfall variation explains 13-19% of the cross sectional variation in migration rates. In the model, the remaining variation in migration will be explained by the realization of idioysncratic income shocks.

higher temporary migration. To show this, I estimate a test for full risk sharing. I estimate the following regression for household i in village v at time t:

$$\log c_{ivt} = \alpha \log y_{ivt} + \beta_i + \gamma_{vt} + \epsilon_{ivt},$$

where β_i is a household fixed effect and γ_{vt} is a village-year fixed effect that captures the total resources available to the village at time t. The intuition of tests of full risk sharing is that individual income should not predict consumption, conditional on total resources (Townsend, 1994).

Table 2 reports the results of the tests. Full risk sharing is rejected. The estimated income elasticity is 0.08. Column 2 interacts the mean level of migration in the village with income. The estimated coefficient is positive and statistically significant: a 10% increase in the mean level of migration in the village increases the elasticity of consumption with respect to income by 0.025. In other words, villages with higher rates of temporary migration have lower rates of risk sharing. While this does not indicate causality, it is again consistent with the joint determination of risk sharing and migration.[20]

4. *Transfers are insurance*

Next I provide evidence that transfers provide insurance, and depend on the history of shocks. Transfers are defined as the difference between income and consumption.[21] A key prediction of limited commitment models is that transfers should depend negatively on the history of transfers (see e.g. Foster and Rosenzweig (2001)). This holds in the ICRISAT data. I run the following specification that links transfers to the stock of received transfers and the income shock (see Foster and Rosenzweig

[20] Results in Table 2 are robust over alternative definitions of household size: defining the number of household members as (adult-equivalent) baseline composition, adjusting for the number of migrants, and adjusting for the number of migrants and trip length. Results available on request.

[21] Results are robust to defining transfers as the difference between income and expenditure, accounting for any change in net asset position. Results are also robust to instrumenting income with rainfall. Results available on request.

(2001)) :

$$\tau_{it} = \alpha_1 y_{it} + \alpha_2 \sum_{j=0}^{t-1} \tau_{ij} + \epsilon_{it}$$

The results, both in levels and in first differences (to control for household-specific predictors of transfers) are shown in Table 3. The coefficient on income is negative, indicating the transfers provide insurance, and the coefficient on the stock of transfers, α_2 is negative, indicating that current transfers depend on the history of shocks, as implied by limited commitment models.

5. *Marginal propensity to consume from migration income is less than 1:*

   Table 4 decomposes the change in household expenditure for migrant households. Although a household increases their income by 30% during the years they send a migrant, total expenditure (consumption and change in asset position) only increases by 60% as much. I do not directly observe transfer data in the dataset, but this shortfall between income and expenditure is consistent with an increase in transfers from the household to the network.[22]

These empirical facts provide some reduced form evidence for a relationship between migration and risk sharing. However, the key feature of the model is the joint determination of risk sharing and migration. In order to quantify this interaction, I now estimate the model structurally.

4 Structural estimation

This section describes identification of the model and the estimation procedure. There are five groups of model parameters to be estimated:

1. *Income distribution in village:* The income distribution in the village determines the income of households if they do not migrate. I allow for idiosyncratic income shocks

[22] Table 4 reports results in per capita terms using the baseline household composition. A concern is this may understate the increase in consumption due to migrants being absent from the household. I rerun an alternative version of this table where I include gross (instead of net) migration income, and add migrant expenditure to the consumption term. Using this definition, household expenditure increases by only 42% of the increase in expenditure. Results available on request.

and a common village-level aggregate shock.

2. *Income distribution if migrating:* The income distribution at the destination determines the income of households if they migrate.

3. *Utility cost of migrating:* The utility cost is a key determinant of migration.

4. *Preference parameters:* The coefficient of relative risk aversion will determine migration. Both the coefficient of relative risk aversion and the discount factor will determine risk sharing.

5. *Heterogeneity parameters:* I aim to match the basic heterogeneity in the data, that households who have more males or less land are more likely to migrate. To match this I allow for two sources of heterogeneity. First, idiosyncratic income to depend on landholdings. Second, migration cost to depend on the number of males in the household.

4.1 Identification

This section details the identification of each group of parameters. I start by discussing identification in a simplified model of migration, and a simplified model of risk sharing. The full model of temporary migration with endogenous risk sharing is complex and it may not be possible to prove identification analytically (in general, structural dynamic models are not non parametrically identified (Rust, 1994)). I use the logic from the simplified models to inform the identification discussion of the joint model of migration with endogenous risk sharing.

4.1.1 Migration under autarky

This section presents a model of migration without risk sharing. Without risk sharing, the migration problem is a standard selection model.[23] Assume household i has land

[23] Park (2014) discusses how to non parametrically identify the extended Roy model. If there was no uncertainty about the migration outcome, then the identification results of his paper would go through and all parameters of interest can be non parametrically identified. However, in my model, agents make a migration decision based on the ex-ante expected utility of migrating. As a result, the identification results

holdings x and number of males in the household z. I assume that income in the village depends on land holdings, $e_v \sim F_{E_V|X}$. Income in the destination is not a function of landholdings, $m \sim F_M$. The utility cost of migrating is a function of the number of males in the household, $d = d(z)$. Households have contemporaneous CRRA utility function $u(c)$.

Household i migrates if:

$$\text{Migrate} = \mathbb{I}\{E_M u(m) - d(z) \geq u(e_v)\}$$

Letting $h(x) = u^{-1}(x)$ denote the inverse of the utility function, this can be written as:

$$\text{Migrate} = \mathbb{I}\{h(F_M, z) \geq e_v\}$$

By assumption, the returns to migration are not a function of household characteristics. Therefore, F_M is identified as it is directly observed.

From the selection equation above, the number of males in a household acts an instrument for migration and allows $h(F_M, z)$ to be identified. The identifying assumption is that the number of males in the household does not affect income (either in the village or in the city) directly. As discussed earlier, this is a strong assumption. However, it is consistent with the observed labor market evidence from the rich database on individual earnings in both the city and the village. Variation in the number of males shifts the returns to migration, which in combination with the observed migration income, F_M, identify the function h. However, the h function contains both the contemporaneous utility function and the cost of migrating and so does not separately identify the contemporaneous utility function from the cost of migrating. This is because households who are on average more risk averse will migrate less. But, households who face a higher migration cost will also migrate less. Although there is variation in the total effect from the observed migration behavior of households with more males, this does not separate the coefficient of relative risk aversion from the cost of migrating.[24]

in Park (2014) paper cannot be directly applied to this model.

[24]One possible way to proceed would be to assume that the cost of migrating is a function of two in-

The last distribution of interest is the income distribution in the village, $F_{E_V|X}$. Here there is a classic selection problem: only the income for households who don't migrate is observed. From the theoretical framework, migration will be negatively selected on income. As a result, only the upper tail of the income distribution is observed. I assume a specific parametric distribution for income in in the village which allows the underlying parameters of the distribution to be identified from the observed truncated income distribution.[25]

4.1.2 Limited commitment risk sharing without migration

Now consider a simplified model of limited commitment without endogenous migration. The model highlights the difficulty of separately identifying the discount factor from the coefficient of relative risk aversion.

Consider an economy where the income process is deterministic and alternating. The agent who is currently rich has an income share α^{Ω} of total resources Y. The income stream for household A is:

$$e^i = \begin{cases} (1-\alpha^{\Omega})Y & \text{if odd period} \\ \alpha^{\Omega}Y & \text{if even period} \end{cases}$$

and vice versa for agent B.

Assume that the two agents have identical initial Pareto weights. In this case, the two state economy will converge to an egodic set where consumption for the rich agent is given by $\alpha^c Y$, for some $\alpha^c \leq \alpha^{\Omega}$. If perfect risk sharing is not feasible the participa-

struments: $d = d(z_1, z_2)$. For example, z_1 could be the number of males in the household and z_2 could be the distance to the nearest large city. If we estimated the model across villages we could use the variation in the distance to the nearest large city (under the assumption that this does not affect either the income distribution in the village nor the income distribution in the city) as a second instrument for migration. This would then let us separately identify the utility function and the cost of migrating. An alternative approach would be to estimate the model within the village, fix one of the coefficient of relative risk aversion or the mean migration cost, and estimate the other from the data.

[25]It could also be possible to use the instrument for migration to non-parametrically identify the home income distribution. A household with very few males will face a high cost of migration, $d(z)$, and so will need to have a lower income at home to migrate. This generates variation in the threshold for the income distribution and therefore variation in the observed income distribution in the village. With large enough support for z, it would be possible to trace out the income distribution in the village to identify $F_{E_V|X}$.

tion constraint for the agent with the high income realization will bind each period and equilibrium consumption is implicitly defined by the following equation:[26]

$$\sum_{j=0}^{\infty} \beta^j (u((\alpha^c)Y) + \beta u((1-\alpha^c)Y)) = \sum_{j=0}^{\infty} \beta^j (u((\alpha^\Omega)Y) + \beta u((1-\alpha^\Omega)Y))$$

$$u(\alpha^c Y) + \beta u((1-\alpha^c)Y) = u(\alpha^\Omega Y) + \beta u((1-\alpha^\Omega)Y)$$

Agents both discount the future, but also value smooth consumption across time. As a result, the net present value of consuming their income stream for the agent who has the good shock today is a concave function of the variability of income, α^Ω. Depending on the value of the discount factor and the coefficient of relative risk aversion, there will either be no risk sharing, incomplete risk sharing, or perfect risk sharing. This is summarized by the following proposition:

Proposition 4.1. *For the two state deterministic economy, given a discount factor β and relative risk aversion γ, there exists a lower bound on the size of the income shock $\underline{\alpha}(\beta, \gamma)$ and an upper bound $\overline{\alpha}(\beta, \gamma)$such that consumption α^c is given by*

$$\alpha^c = \begin{cases} \alpha^\Omega & \text{if } \alpha^\Omega < \underline{\alpha}(\beta,\gamma) \quad \text{(Autarky)} \\ \alpha^c(\alpha^\Omega, \beta, \gamma) & \text{if } \alpha^\Omega \in [\underline{\alpha}(\beta,\gamma), \overline{\alpha}(\beta,\gamma)] \quad \text{(Imperfect risk sharing)} \\ 0.5 & \text{if } \alpha^\Omega > \overline{\alpha}(\beta,\gamma) \quad \text{(Perfect risk sharing)} \end{cases}$$

Further, the partial derivatives of α^c with respect to its arguments are signed as following:
$\alpha^c_1(\alpha^\Omega, \beta, \gamma) < 0, \alpha^c_2(\alpha^\Omega, \beta, \gamma) < 0$, and $\alpha^c_3(\alpha^\Omega, \beta, \gamma) > 0$.
Proof: See Appendix B.1

This proposition says that whether perfect risk sharing, imperfect risk sharing, or no risk sharing is observed will depend on the discount rate, the coefficient of risk aversion, and the income process. If imperfect, then risk sharing improves (α^c gets decreases and so consumption becomes more equal across the two agents) if agents are more risk averse or income is riskier (and vice versa).

[26]Perfect risk sharing is feasible if $(1+\beta)u(0.5Y) \geq u(\alpha^\Omega Y) + \beta u((1-\alpha^\Omega)Y$.

Separately identifying the discount factor from the coefficient of relative risk aversion is challenging because they move in opposite directions: if agents are more risk averse they value insurance more. If agents care more about the future, they also value insurance more. As a result, if imperfect risk sharing is observed it is possible to identify either the discount factor or the coefficient of relative risk aversion, but not both. However, if perfect risk sharing or no risk sharing is observed, then we cannot identify either parameter: perfect risk sharing could occur either because agents have a very high discount factor or are very risk averse, or because income is very risky.

For the more general dynamic limited commitment model, it may be possible to separately identify the time discount factor and the coefficient of relative risk aversion using additional intertemporal moments. However, in general, it is a very challenging problem to separately identify these two parameters (see, for example, the extensive discussion in Guvenen and Smith (2014)). In the estimation, I will proceed by fixing the coefficient of relative risk aversion and estimating only the discount factor. I then provide extensive robustness over the choice of the fixed parameter.

4.2 Identification of the dynamic model

The simplified models discussed above are helpful for thinking through the variation in the data. However, the full model of temporary migration with endogenous risk sharing is substantially more complex. To identify the dynamic model I make four parametric assumptions:

1. Village income follows a known distribution function $F^*_{E_V|X}$.
2. Destination income follows a known distribution function F^*_M
3. Utility is CRRA, $u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$
4. The coefficient of relative risk aversion is known $\gamma = \gamma^*$

Table A summarizes how I match each parameter to the data. I estimate the model for each village separately. For each village, I estimate 8 parameters, and set 3 parameters exogenously. Because I allow for heterogeneity in land holdings and household composition when estimating the model, it is necessary to have a large enough sample size within each village. For this reason, I drop village 6 because its sample size is only 32 households. The final structural estimation sample is 5 villages. In total, I estimate 8 parameters for each village, yielding a total of 40 parameters to be estimated, and set 3 exogenously. The parameter vector $\theta = \{\theta_{\text{estimated}}, \theta_{\text{exogenous}}\}$ is a vector of 43 parameters which fully characterizes the risk sharing and migration model.

Table A: Parameter vector for structural model

Type of parameter	*Symbol*	*Main source of variation in data*
Income distribution in village	μ_v	Mean income of non migrants
	σ_v	Standard deviation of income for non-migrants
Income distribution if migrating	$\mu_{\text{mig},v}$	Mean income of migrants
	$\sigma_{\text{mig},v}$	Standard deviation of income for migrants
Utility cost of migrating	d_v	Mean households migrating
Discount factor	β_v	Correlation between income and consumption
		Mean consumption of migrants
		Mean consumption of non migrants
Heterogeneity parameters	$\alpha^{\mu}_{\text{land},v}$	Mean income of non-migrant land owners
	$\alpha^{d}_{\text{male},v}$	Mean male households migrating
Parameters set exogenously		
Scaling parameter good agg shock	μ	1.2
Coefficient of relative risk aversion	γ	1.6
Income share from migration		0.6

Notes: Table summarizes how the parameters match to data moments. Parameters with a v subscript are estimated at the village level.

4.2.1 Specific moments matched

This section discusses how the model parameters map to the moments in the data.

Village income distribution: Household income depends on the aggregate income shock, idiosyncratic income shock, migration decision and migration income. Exogenous variation in income comes from monsoon rainfall, which determines the aggregate state of the world in the village. I make parametric assumptions for the income distribution faced by the households in the village and in the city.

Total household income depends on the migration decision. If the household does not migrate, their income comes only from their village income draw, e_{ivt}. If the household migrates, the migrant receives migration income draw, m_{ivt}, and total household income is a combination of income earned by the migrant and by the non-migrants.

Each household i in village v receives an income at time t that has an idiosyncratic (ϵ) and aggregate (ν) component:

$$e_{ivt} = \nu_{vt}\epsilon_{ivt}.$$

The idiosyncratic shock is an iid draw from a village-specific log-normal distribution with mean μ and variance $\sigma^2_{\text{idio,v}}$:

$$\log(\epsilon) \sim \mathcal{N}(\mu_v, \sigma^2_{\text{idio},v}).$$

I allow the village income distribution to be a function of land holdings. I scale the mean of the income distribution by $\alpha^{\mu}_{\text{land}}$, estimated structurally, if the household is in the top half of the land holding distribution within the village.

Village aggregate shock: The source of the aggregate shock for the villages is the exogenous realization of rainfall. I use a historical rainfall database covering the years 1900-2008 to compute the long run rainfall distribution and to estimate the magnitude of the aggregate shock. I estimate the effect of the rainfall shock on output using the earlier VLS1 data, and then take this income process as given for the estimation.[27] Appendix Table 3 examines the effect of an aggregate shock on rainfall for the 1975-1984 ICRISAT data. I compute 4 different shock measures: the arrival of the monsoon (measured as the first day after June 1 with more than 20 mm of rain, following Rosenzweig and Binswanger (1993)), a rainfall shock that falls in the 10% percentile of the long run rainfall distribution, a rainfall shock in the 20% percentile and a shock in the 50% percentile. The monsoon start date is a strong predictor of rainfall. However, to calculate the monsoon

[27] It is potentially feasible to estimate the aggregate shock process within the estimation procedure. However, as I only observe 4 realizations of the aggregate shock for each village, any such estimation would be very noisy. As a result, I take this income process as given.

start date it is necessary to have data on daily rainfall, and this was unfortunately not collected over 2001-2004 for the ICRISAT villages. Instead, I define the aggregate shock as a rainfall event falling below the 20% percentile of the long run rainfall distribution. This reduces output by 23%, and occurs with probability 0.28. I set the scaling parameter to 0.2 and the probability of the shock to 0.3 for the structural estimation.[28] I then use the actual rainfall realization over the years 2001-2004 to characterize the realized aggregate state in the model.

Migration income distribution: If agent i migrates from village v they receive an income draw m from a log-normal distribution with mean $\mu_{\text{mig,v}}$ and variance $\sigma^2_{\text{mig,v}}$. I assume that all agents face the same ex-ante income distribution if they migrate:

$$\log(m) \sim \mathcal{N}(\mu_{\text{mig,v}}, \sigma^2_{\text{mig,v}}).$$

To implement the estimation I discretize both income processes. To do this, I follow Kennan (2006), and choose points of support in the distribution such that there is equal probability placed on each support point.

Utility parameters: I assume CRRA preferences. The discount factor β and the coefficient of relative risk aversion γ both affect risk sharing: households who are more patient can share idiosyncratic risk more easily, and agents who are more risk averse also prefer to share risk. Risk aversion also affects migration, as agents who are more risk averse prefer certainty over uncertainty and require larger expected gains in order to migrate. As per the discussion above, it is very difficult to separately identify the discount factor for the coefficient of relative risk aversion.

I proceed by setting the coefficient of relative risk aversion and then estimating the discount factor to match the risk sharing moment. The baseline estimates set the coefficient of relative risk aversion equal to 1.6 to match the estimate in Ligon et al. (2002), and robustness over this value is performed. To capture risk sharing, I use the correlation between income and consumption as the summary risk sharing moment. I also include the mean of consumption (for both migrants and non migrants).

[28] As a robustness test I also define an aggregate shock as below-median rainfall. This occurs with $\pi = 0.49$, and reduces income by 10.4%.

Cost of migrating: The direct utility cost, d, is unobservable to the econometrician but is key to the household's decision to migrate. d is identified by matching mean migration rates. Intuitively, if the direct utility cost were zero there would be a threshold income level in the village below which agents would migrate. Increasing d increases this threshold and increases the share of the village who have income below this threshold.

In the data, the number of males in the household is a strong prediction of migration. To match this fact, I allow for heterogeneity in the migration cost by the number of males in the household. I assign a dummy indicator $\mathbb{I}_{\text{male}}$ if the household has more males than the median for all households, and estimate a scaling parameter α_{male} corresponding to the utility cost for these households. The specific moments I match in the data are the mean migration rate overall and the mean migration rate of many-male households.

4.2.2 Simulation analysis

As a check on how well the identification arguments for the simple model apply to the dynamic model I simulate the dynamic model for a range of parameter values. I vary each parameter of interest and then plot the responses of each of the 8 main moments as the parameter changes. For each plot, I normalize all moments to have the same relative magnitude for the baseline value of the parameter, so the plot can be interpreted as the relative effect on each moment. For each panel of the plot, I bold the moment that is most closely related to the parameter of interest. The results are plotted in Appendix Figure 1.

The figure shows that the intuition from the simple model holds for the dynamic case. It also highlights the complex interactions between outcome variables in the dynamic model. For example, Panel A shows the effect of increasing the mean of the village income distribution. The main moment that captures this parameter is the mean income of non-migrants, which is bolded. However, as village income increases, there are endogenous responses both from migration and from risk sharing. First, migration rates decreases, as the relative returns to migration drop. Both the mean migration rate and the mean migration rate for many-male households decreases (the two lines are overlaid after the initial point: overall migration and migration of many male households decrease at the same relative rate). Second, as village income increases households get richer, which improves risk sharing. The risk sharing measures therefore decreases, reflecting that consumption depends less on income.

Panel B shows the effect of changing the standard deviation of the income process. The primary moment that this parameter affects is the variance of non-migrant income. However, changing the variance of the income process also changes risk sharing. As the variance of income in the village increases insurance becomes more valuable, and risk sharing endogenously improves, decreasing the risk sharing coefficient (which measures the correlation between income and consumption). This is shown in the plot. The relationship between the discount factor and the risk sharing coefficient is clear from Panel F. As the discount factor increases, the dominant effect is a reduction in the correlation between income and consumption, along with an endogenous reduction in migration as risk sharing improves.

4.3 Estimation

I estimate the model using simulated method of moments (McFadden, 1989). The aim of the structural estimation is to generate a series of simulated data which matches the observed data as closely as possible. I construct a vector of moments from the data, q_s, relating to migration, income, and risk sharing. I then solve the model for a specific value θ of the underlying parameters, generate a simulated dataset, and construct the same moments from the simulated data. This section discusses the model solution and estimation algorithms. Full details of both algorithms are contained in Appendix C.

4.3.1 Algorithm to solve the limited commitment model

The model presented in Section 2 was a two household model. The average village has approximately 400 households of which I observe a sample of approximately 80 in the dataset. The model can be extended to N agents by including each agent's relative Pareto weight as an additional state variable. However, this is computationally intensive. I follow Ligon, Thomas and Worrall (2002) and other empirical applications of the limited commitment model (Laczo, 2015), and construct an aggregated "average rest of the village" household by taking the mean over N households who have the same income process.[29] The average rest of the village depends on the specific realization of the idiosyncratic shock for the household. For each state of the world s I construct the average village member by assigning the income realization such that the sum of household H and the rest of the village is equal to the average level of resources in the economy. This assumes that the rest of the village is, on average, sharing risk perfectly between one another. I show in Appendix C that this approximation method is very close to the continuum solution for a simplified version of the limited commitment model.[30]

The limited commitment model is characterized by state-dependent intervals that give the lower and upper bounds for Pareto weights for each state of the world (Ligon et al. (2002)). In my case, I need to solve the model in two parts to find these intervals. First, the ex-ante value function is solved on a grid indexing the state of the world in the village and the household's Pareto weight, (s, λ). Second, the ex post value function is solved on a grid indexing the state of the world in the village, the households Pareto weight, the state of the world in the destination and the migration decision, $(s, \hat{\lambda}, q, j)$. This procedure generates two sets of interval containing the lower and upper bounds of the endogenous Pareto weights such that incentive compatibility constraints are satisfied: ex ante intervals, $[\underline{\lambda}_s, \overline{\lambda}_s]$, $\forall s$, and ex post intervals, $[\underline{\hat{\lambda}}_{sqj}, \overline{\hat{\lambda}}_{sqj}]$, $\forall s, \forall q, \forall j$.

Once the intervals have been computed, I calculate the transition rule for the Pareto weights such that the market clearing condition (that total consumption across all households equals total income across all households) is satisfied for all states. To do this, I compute transition matrices between the ex-ante and ex-post states in the current period, and then between the ex-post outcome in the current period and the ex-ante state in the following period. For agents that have binding constraints, whether in the ex-ante or ex-post state, the Pareto weight is updated to the lower bound of the relevant interval. For agents that don't have binding constraints their Pareto weight is a value inside the interval. The

[29] I take $N = 20$ for the main specification; Appendix Table 5 shows robustness over the choice of N.

[30] Assuming that the rest of the village shares risk perfectly may seem to be a contradiction. However, the assumption that the rest of the village is sharing risk perfectly is only used to generate the upper bound of the interval. This upper bound is not used when computing simulated consumption: for each income realization an economy-wide budget constraint needs to hold, and so consumption for individuals who do not have a binding participation constraint will depend on their previous Pareto weight and the consumption of all other members so that the budget constraint is satisfied.

first order conditions yield that the ratio of marginal utility growth across any two unconstrained agents is constant; this implies that agents who are unconstrained this period have a Pareto weight which is their previous Pareto weight multiplied by an economy-wide scalar such that the first order condition is satisfied across all agents (agents with a binding constraint have their Pareto weight determined by the lower bound of the relevant interval). The algorithm solves for the value of the scaling factor such that the invariant distribution of agents over the ex-post state of the world $(s, \hat{\lambda}, q, j)$ is equal to the invariant distribution of earnings (both village earnings, $e(s, \hat{\lambda}, q, j)$, and earnings from migration, $m(s, \hat{\lambda}, q, j)$, accounting for the invariant distribution of which agents migrate).[31] This procedure ensures that the aggregate resources constraint is satisfied across all households and all ex post states.

The specific steps to do this are:

(a) Solve the limited commitment algorithm for 2 households (household A and the "rest of the village" household) to find the ex-ante intervals $[\underline{\lambda}_s, \overline{\lambda}_s] \forall s$, and the ex-post intervals $[\underline{\hat{\lambda}}_{sqj}, \overline{\hat{\lambda}}_{sqj}]$, $\forall s, \forall q, \forall j$ and the migration rule $\mathbb{I}(s, \lambda)$. In this step, the fixed point of the migration decision (which determines the total resources available to the network) is found.

   (a) Guess an initial migration rule $\mathbb{I}_0(s, \lambda)$. Using this migration rule, construct the total resources available to the network.

   (b) Then, given these total resources, solve the ex-post allocation problem to find the constrained efficient level of transfers.

   (c) Then, solve the ex-ante decision to find the optimal migration decision, $\mathbb{I}_1(s, \lambda)$ satisfying the ex-ante participation constraint.

   (d) Complete Steps (a)-(c) until a fixed point of the migration decision is found.

(b) Once the fixed point of the problem is found, use the lower bounds of the computed ex ante and ex-post intervals to compute a transition matrix between ex ante and ex post states and the invariant distribution over income and earnings. The Pareto

[31] An alternative procedure to impose the aggregate budget constraint is inside the simulation step instead of through adjusting the transition matrix. This is the approach taken by Laczo (2015).

weights of constrained agents are pinned down by the lower bound of the interval. The Pareto weights of unconstrained agents are updated to be the previous Pareto weight rescaled by state-specific factors β_s such that all agents have their participation constraint satisfied. In this step, the values of β_s such that market clearing occurs are found for each value of the state.

(a) Guess an initial rescaling factor for each state, $\beta_s^0, \forall s$.[32]

(b) For each grid point $(s, \hat{\lambda}, q, j)$ compute the ex-post Pareto weight for each possible ex post state of the world. This will be the lower bound of the interval if the participation constraint is binding. If the participation constraint is not binding this will be the current value of the Pareto weight, multiplied by an economy-wide scalar.

$$\hat{\lambda}_0(s, \lambda, q, j) = \max[\underline{\lambda}_{sqj}, \beta_s^0 \lambda]$$

(c) Now compute the ex-ante Pareto weight for the following period. This will be the lower bound of the relevant interval if the participation constraint is binding. If the participation constraint is not binding this will be the current value of the ex-post Pareto weight.

$$\lambda_1(q, j, r) = \max[\underline{\lambda}_r, \hat{\lambda}_0(s, q, j)]$$

(d) Construct the transition matrices $Q_{\text{ex-ante,ex-post}} : (s \times \lambda) \times (s \times \lambda \times q \times j) \to [0, 1]$ and $Q_{\text{ex-post,ex-ante}} : (s \times \hat{\lambda} \times q \times j) \times (r \times \lambda') \to [0, 1]$. Using these transition matrices, find the invariant distribution of agents over the ex post states $\hat{\phi}(s, \hat{\lambda}, q, j)$.

(e) Compute aggregate net demand in the economy. Iterate on β_s until the budget constraint is satisfied for each state of the world.

[32] Because a binding participation constraint in either the expost or the exante problem resets the Pareto weight it is only necessary to search for one economy-wide scaling factor, not a separate factor for the exante and the expost state.

4.3.2 Algorithm to estimate the model

After completing the above step and constructing the transition matrices the last step of the estimation is to simulate a wide cross section and long time series of agents, and compare simulated moments to real data moments. For a given value of the parameter vector, θ, the solution of the limited commitment model yields the migration rule, updating rule for the Pareto weight, and transfer rule, for each state of the world. It is necessary to supply an initial Pareto weight. To minimize the effect of this initial weight, I construct a long time series and discard the initial periods.

The algorithm is as follows:

1. Construct the vector of data moments q_s.

2. For the given θ solve the model and find the transition matrices $Q_{\text{ex-ante,ex-post}}$ and $Q_{\text{ex-post,ex-ante}}$.

3. Construct a history of $T-4$ aggregate shocks for each village. Use the actual realization of the aggregate shocks in the data for the last 4 years of the series.

4. Draw a history of T idiosyncratic shocks for N individuals in each village. Together, the idiosyncratic shock and aggregate shock determine the state of the world s for each T.

5. Set the initial ($t = 0$) Pareto weight to a random number $x \in [0, 1]$ for each household.

6. Use the transition matrices to simulate migration, income and consumption for the N agents over T years.

7. Discard the first $T-4$ years of data. Compute the simulated moments $Q(\theta)$ using N individuals over 4 years where the aggregate shocks in the simulated data match the aggregate shocks in the data.

8. Compute the criterion function $(Q(\theta) - q_s)'W^{-1}(Q(\theta) - q_s)$, where W is a positive definite weighting matrix (the identity matrix is used in the estimation). Standard

errors are calculated by first approximating the discrete migration choice with a continuous formula, following Horowitz (1992); Keane and Smith (2004), and then utilizing numerical gradient methods to compute the covariance matrix.

5 Structural Results

This section presents the structural estimation results and performs a counterfactual policy analysis. The structural results highlight why it is quantitatively important to consider migration and risk sharing jointly. First, I show the implications of endogenous migration for estimating the returns to migration. I then use the model to quantify the comparative statics between migration, risk sharing and welfare. Finally, I show that the joint determination of migration and risk sharing has key implications for policy.

Table 5 shows the fit of the model to the data by village. The J test overidentification test is not rejected for any of the five villages. The parameter point estimates from the structural estimation are provided in Table 6. The parameters differ across village. This is to be expected: for the income parameters, each village has its own income process and additionally also sends migrants to different migrant destinations. The migration cost is also estimated at the village level and captures all the costs associated with migration; this also plausibly varies by village (for example, some villages are more or less connected to main migration destinations).

Migration has a higher mean return than village income (mean of the log-normal distribution is estimated to be 1.6 compared with 1.2), but is considerably riskier (standard deviation of 1.2 compared with 0.8). The model matches migration rates with expected income differentials through a utility cost of migrating. The mean cost, 0.22, is substantial, equivalent to 21% of mean household consumption. For households with many males, who face a lower utility cost, the cost is estimated to be approximately 18% of mean consumption (scaling factor of -0.56). The estimated discount factor is 0.58. This is a low value, especially compared with literature in developed countries which estimate an annual discount factor closer to 0.9 (see, for example, Gourinchas and Parker (2002)). The key moment pinning down the discount factor is risk sharing; with a higher value of the time discount factor then risk sharing would be better than what is observed in the data. While the estimated value for β is low, it is not a priori clear what the discount factor should be for low income countries. The point estimate of 0.58 is at the upper end of the range of 0.4-0.6 elicited experimentally from individuals in the ICRISAT villages (Pender, 1996). A discount factor of 0.58 would be equivalent to an interest rate of 75% in a perfect market economy, which is reasonable with respect to interest rates charged by micro finance organizations.[33] Additionally, Ligon et al. (2002) estimate a discount factors between 0.7-0.95 in their study of the same ICRISAT villages. To further explore the discount factor magnitude I run two robustness tests: I allow for an autoregressive income process and I change the value of the coefficient of risk aversion. The baseline specification fits the model best (see the results in Appendix Table 5).

5.1 Selection and returns to migration

Both permanent heterogeneity and temporary income shocks affect migration. The selection of households into migration, as a function of their village income, is shown in Figure 3. The shaded area on each graph shows the selection of households into migration, and shows the amount of selection into migration on income. I separate out the income distribution for good aggregate shocks and for bad aggregate shocks. Migration depends on the realization of the aggregate shock. Migration allows the network to smooth aggregate shocks, with the migration rate for a bad aggregate shock 5 percentage points higher than the migration rate with a good aggregate shock. Migration also depends on permanent characteristics of households. Landed households have a higher income in the village, and so migrate less. Households with many males have a lower cost of migrating, and so migrate more.

Table 7 shows the effect of migration on migration and village income. There are three results in the table. First, migration has a significant return. The mean income of migrant households is 5600 rupees per equivalent adult (approximately $110 USD). Households, on the whole, would have been considerably worse off had they not migrated. Counter-

[33] For example, micro finance APRs are 100% in Mexico Angelucci et al. (2015), 60% in the Philippines Karlan and Zinman (2011), 30% in India Banerjee et al. (2015).

factual income (the income the household would have had in the village) is close to half of actual income, at 2900 rupees ($58 USD). Second, migration is risky. Ex-post, not all migrant households are better off migrating than they would have been staying in the village. I estimate 67% of migrant households have higher income from migrating than they would have if they had not migrated. However, 33% are ex-post worse off. This number is consistent with the experimental findings in Bryan, Chowdhury and Mobarak (2014) who estimate a 10-20% risk of "failure" from migration. The third result is that endogenous migration biases the observed returns to migration. The income of households who choose not to migrate is 5800 rupees per adult equivalent household member (approximately $116 USD). A naive estimate of the returns to migration would be to compare the income of non-migrants to income of migrants. This would yield a negative return to migration: non-migrants have a household income of 5800 rupees, compared with migrant income of 5600 rupees.[34] However, this is not the correct comparison. The true return to migration is the comparison of the income migrant households would receive if they did not migrate; in this case, 5600 rupees compared with 2900 rupees.

5.2 Theoretical comparative statics

I now quantify the three comparative statics linking migration, risk sharing and welfare:

1. Reducing the cost of migration increases the correlation between income and consumption (i.e. decreases risk sharing) by 8 percentage points.
2. The welfare effect of introducing migration is large under autarky (equivalent to a 24% consumption-equivalent gain). However, the welfare effect of introducing migration is lower with exogenously incomplete markets and is lower again (in fact, is negative) with endogenously incomplete risk sharing.
3. Allowing risk sharing transfers reduces the migration rate by 21 percentage points compared to the migration rate if households were in autarky.

[34]This difference holds if the compositional effects (i.e. permanent characteristics) of non-migrants and migrants are controlled for.

5.2.1 Reducing the cost of migration reduces risk sharing

Theoretically, the effect of reducing the cost of migration on risk sharing is ambiguous. On one hand, a lower cost of migration increases the outside option of households, decreasing risk sharing. On the other hand, a lower cost of migration allows the network to smooth aggregate shocks, increasing risk sharing. I consider the introducing migration into the model compared to the case where migration was not possible (a reduction in the exogenous cost of migrating from a very large number such that no household ever migrates to a finite cost that was estimated). The result of introducing migration on risk sharing in Table 8. On average, the correlation between income and consumption is 14.4% when migration costs are at a level such that no-one migrates, whereas with the cost estimated from the model, this correlation is 22.4%. With a lower cost of migration, households are more exposed to income risk, and I find the crowding-out effect dominates. The net effect of reducing the cost of migration is to reduce risk sharing by 8 percentage points%. Columns (3) and (4) make the same comparison with and without lower costs of migration over the sample of agents who do not migrate. The households who do not migrate have the same income in both states of the world, so the only change that occurs is through the change in the distribution of consumption for these households. The same pattern holds.

The overall correlation masks a substantial degree of heterogeneity within group. The group that has the largest change in risk sharing is the households that have many males, and therefore can more easily migrate. For example, the correlation between income and consumption for landed households with many males increases from 12.7% to 21.4% with the lower cost of migration. This is the group of households who are least likely to migrate because they face high opportunity costs as well as large migration costs.

5.2.2 Decomposition of the welfare effect of reducing the cost of migration

Migration both changes the resources available to the village, but also endogenously changes risk sharing. The net welfare effect of reducing the costs of migration can be decomposed into an income effect and a risk sharing effect. To decompose the welfare effect I contrast a model with *endogenously* incomplete markets to a model with *exogenously* incomplete markets. Specifically, I consider a model where households can borrow and save a risk-free asset (as in Deaton (1991); Aiyagari (1994); Huggett (1993)). The key difference between the two environments is that a lower cost of migration does not alter the structure of the insurance market if markets are exogenously incomplete as it does when markets are endogenously incomplete.[35] For ease of comparison I also show the effect of migration under autarky, where households do not have access to any risk-smoothing technology.

The results for three regimes are shown in Table 9. The welfare benefits of reducing migration costs are largest when households are in autarky and do not have access to any risk smoothing technology: introducing migration is equivalent to a 24.0% increase in average consumption. The benefit is positive with borrowing and saving, but smaller: households already could mitigate income shocks and hence the additional mechanism of migration is less valuable. I estimate the consumption equivalent gain to be a 17.0% increase in average consumption. Finally, when markets are endogenously incomplete, the welfare benefit of reducing the cost of migration is smaller again. First, migration is an additional mechanism to informal risk sharing, so the level effect of migration is smaller than under autarky. Second, the option to migrate endogenously changes the outside option of households and reduces informal insurance, so the welfare benefit is smaller than under borrowing-savings. I estimate the benefit of reducing the cost of migration under limited commitment to be negative, equivalent to a 9.9% decrease in consumption. Contrasting endogenous to exogenous risk sharing, the consumption-equivalent gain from migration is 18.9 percentage points% lower.

The table also shows the heterogeneous effects of migration by subgroup. The largest relative benefits from migration are to the households with little land and many males who are most easily able to migrate, and households with land and many males who were on average wealthier and so benefit by being able to keep relatively more of their income in the high states of the world when risk sharing worsens. However, under endogenous

[35] I set the risk free interest rate to 0.30 and an exogenous borrowing constraint of approximately 50% of average annual income.

risk sharing both groups face a decrease in consumption: the landed households with many males has a loss equivalent to 5.0% of consumption and landless households with many males a loss equal to 5.3% of consumption.[36]

5.2.3 Increasing the ease of risk sharing reduces migration

If households are able to make transfers to share risk, the migration decision no longer depends on the gross income differentials between the village and the city, but the post-transfer income differential. I consider introducing risk sharing into the model (i.e. a reduction in the cost of inter-household transfers for a cost of 100% to a cost of 0% or moving from a autarkic world where no transfers are ever made, to a world where transfers can occur costlessly). There are two potentially offsetting effects of reducing the costs of transfers on migration: a home effect, that reduces migration, and a destination effect, increasing migration. Migration rates under alternative risk sharing regimes are presented in the first panel of Table 9. With endogenous risk sharing, the mean migration rate is 14.3%. Under autarky, migration rates would be 35.3%. The net effect of introducing risk sharing (for example, by reducing the cost of inter-household transfers) is to reduce migration by 21 percentage points. Column (2) of the table estimates the migration rate under borrowing-saving; it is slightly lower than autarky, at 31.5%. Under this latter regime, agents are able to self-insure negative migration outcomes through asset accumulation, and can keep the full amount of migration-related earnings because they do not need to make risk-sharing transfers.

[36] A large part of these welfare losses arise from the fact that households who migrate must pay a utility cost of migrating. The utility cost is sunk at the time that the expost constraints are computed and so only affects that decision to migrate and the value of the exante outside option, but is not directly insured by the network in the case of a low migration outcome. Setting the migration cost equal to zero, but keeping migration rates at the same level as estimated, yields a positive welfare gain of 6.5% under endogenous risk sharing (44.6% and 17.0% under autarky and exogenously incomplete markets, respectively). Another hypothesis is that this negative welfare gain is coming from the large variance of income if a household migrates, but this does not explain the differential gain across the three market structures considered.

5.3 Robustness

I run several robustness tests for the model, which are summarized in Appendix Table 5. First, I reestimate the model for different values of the coefficient of relative risk aversion. As discussed above, the coefficient of relative risk aversion and the discount factor are highly negatively correlated, making it difficult to separately identify the two parameters. The baseline results set the coefficient of relative risk aversion to 1.6. Increasing the correlation of relative risk aversion to either 2 or 2.5 decreases the estimated discount factor (to 50.2% and 47.7% respectively) as expected. The results on risk sharing and welfare from introducing migration are robust: the net welfare gain from introducing migration is 96.6% of the original. The second robustness check is to investigate the low estimated discount factor by allowing the income process in the village to be autoregressive. Risk sharing is determined by agents with high income shocks, and so persistent shocks increases the value of autarky for an agent that has a high income shock today, reducing risk sharing. When I estimate the model with an autoregressive coefficient of 0.1 the discount factor slightly increases from 58% to 60%. However, I find little evidence in the data that income is in fact autoregressive and the overall model fit worsens with autocorrelation in income.[37] The third robustness run of the model is to estimate the model assuming a different number of households in the village. This affects how well insured the average 'rest of village' household is (averaging over more households reduces the idiosyncratic component of income), lowering risk sharing. The main difference is that the estimated discount factor is slightly higher, at 63%. The effects on the welfare effect of introducing migration (96.6% of the original level) are robust to the baseline run. However, this parameterization does not fit the data as well (J statistic of 3.2 vs 1.8).

5.4 Policy implications

I now consider the policy implications of the joint determination of migration and risk sharing. I first examine the Indian Government's National Rural Employment Guarantee

[37] I estimate a model of lagged income on household income using the VLS1 data, including household fixed effects and correcting for dynamic panel bias. The coefficient on lagged income is small (0.08) and is not statistically significant. Results are in Appendix Table 4.

Act (NREGA), a large-scale public works program. I then examine a set of separate policies that target migration itself: increasing economic growth in the city; decreasing the utility cost of migrating; and decreasing the variance of migration income.

5.4.1 Effect of the NREGA policy

The NREGA, introduced in 2005, is the largest rural employment scheme in the world, providing 55 million households with employment during 2010-11 (Government of India, 2011). The NREGA guarantees 100 days of work to each rural household. I model the scheme as a form of insurance, providing a minimum income level in the village, and examine the effect on migration and risk sharing.[38]

What is the welfare effect of the change in risk sharing and the change in migration? Other studies have documented how public transfers may crowd out informal risk sharing and hence reduce the welfare gains of policies (Attanasio and Rios-Rull, 2000; Albarran and Attanasio, 2003; Golosov and Tsyvinski, 2007; Thomas and Worrall, 2007; Krueger and Perri, 2010). I show this effect is present in my model. The break-down in informal risk sharing crowds out the welfare gain of the policy. However, in my model, there is an additional dimension that is crowded out. The rural employment scheme increases income in the village, directly substituting for migration. Comparing the effects of the policy under exogenously incomplete markets to the effect under endogenously incomplete markets, the welfare gain of the policy is 50-65% lower after household risk sharing and migration responses are considered. The key implication for policy is that households will adjust both risk sharing and migration, and it is necessary to consider both margins to fully understand the welfare effects of this development policy.

Table 10 shows the effect of the NREGA policy under alternative economic environments. I first consider the case when there is no migration. The policy will have the largest effect if households are in autarky and do not have access to any income-smoothing technology. In this case, the NREGA will act as a targeted income transfer. Column (1) shows

[38] What follows can be interpreted as an ex-ante evaluation of the NREGA policy. Ex-post there were many difficulties and irregularities in implementing the NREGA scheme. Additionally, (Imbert and Papp, 2015a) show that the NREGA has general equilibrium effects on wages. I abstract from this effect in the analysis.

that under autarky and no migration the welfare benefit of the NREGA is equivalent to a 22.0% increase in average consumption. In comparison, if households are able to smooth income shocks, the marginal benefit of the NREGA income transfer is smaller. I examine this in two steps: a 'level' effect, by examining autarky to exogenously incomplete insurance, and then a 'crowding out' effect', comparing exogenously incomplete insurance to endogenously incomplete insurance. Column (2) recomputes the benefit if households have access to borrowing-saving (exogenously incomplete markets). The welfare benefit of the policy is still large and positive, but smaller in magnitude than autarky: 12.4%. This is because households were already able to smooth some of the welfare fluctuations of the income shocks. Column (3) estimates the effect of the policy under limited commitment. This takes into account the endogenous reduction in informal insurance as a result of the NREGA. The welfare effect of the policy is smaller than under exogenously incomplete markets, 4.7%, due to the crowd-out of informal insurance.

Table 10 shows the welfare effects under migration. The NREGA increases income in the village, reducing migration. The welfare effect of the NREGA policy is smaller, because migration is already a mechanism for households to smooth income shocks: households substitute away from migration towards the publicly provided insurance. The benefit of the scheme is 4.8% if households are autarkic. Note the difference in the effect of the NREGA when households are autarkic: 22.0% without migration, and 4.8% with migration. Accounting for endogenous migration is important, regardless of the insurance environment. Columns (5) and (6) repeat the analysis for exogenously incomplete and endogenously incomplete insurance. The same pattern as in the environment without migration holds. The benefit of the policy when households can borrow or save is 4.0%, and then once the endogenous change in insurance is taken into account, the final welfare benefit of the NREGA is 2.1% under limited commitment with migration.

The cost of the policy can be approximated from the migration response. If there is relatively less migration, this means that fewer people are migrating, as so more households will take up the NREGA work offer. The third panel of Table 10 shows that the largest drop in migration is when markets are endogenously incomplete. Under limited commitment, the overall migration rate is 86% of what it would have been without NREGA (i.e.

a reduction of 14%) compared with 90% when markets are exogenously incomplete (i.e. a reduction of only 10%). Therefore, not only is the benefit smaller, but the cost is also larger.

6 Conclusion

Economists have long studied the complex systems of informal insurance between households in developing countries. Informal insurance is important because formal markets are generally absent in these environments, leaving households exposed to a high degree of income risk. However, studies of informal insurance have generally not considered that households have access to other risk-mitigating strategies. This paper studies temporary migration, a phenomenon that is both common (20% of rural Indian households have at least one migrant) and economically important (migration income is more than half of total household income for these households). Temporary migration provides a way for households to self-insure, hence it may fundamentally change incentives to participate in informal insurance. At the same time, informal insurance changes the returns to migration. For this reason, this paper has argued that it is necessary to consider the migration decision of the household *jointly* with the decision to participate in informal risk sharing networks.

The analysis proceeds in three steps. First, I characterize a model of endogenous limited commitment risk sharing with endogenous temporary migration, in which risk sharing and migration are jointly determined. In the limited commitment model, the key determinant of risk sharing is the household's outside option. Migration changes the outside option, hence changing the structure of endogenous risk sharing. I demonstrate how the welfare effect of reducing the costs of migration can be decomposed into an income effect and a risk-sharing effect. I then show how improving access to risk sharing alters the returns to migration, and determines the migration decision.

Second, I estimate the model structurally on the new wave of the ICRISAT panel dataset. I allow for heterogeneity in landholdings and household composition to match migration rates across groups. The quantitative results are: (1) reducing migration costs reduces risk sharing by 8 percentage points; (2) contrasting endogenous to exogenous risk sharing, the consumption-equivalent gain of reducing migration costs migration is 18.9 percentage points lower; (3) improving access to risk sharing reduces migration by 8 percentage points.

Third, the fact that households make both risk sharing and migration decisions jointly has key implications for development policy. For example, policies that address income risk will have direct effects, but may also have indirect effects, such as crowding out informal risk sharing. It is important to account for both the direct and indirect effects in welfare calculations. This point has been made for other contexts, such as public insurance in the PROGRESA villages (Attanasio and Rios-Rull, 2000). I demonstrate that it is also important to consider how policy affects migration decisions. Using the example of the Indian Government's NREGA policy, the largest-scale public works program in the world, I show the policy substitutes for informal insurance, reducing risk sharing. In addition, the rural employment scheme increases income in the village, substituting for migration. I illustrate how the welfare benefits of this policy are overstated if the joint responses of migration and risk sharing are not taken into account. The welfare gain of the policy is 55-70% lower after household risk sharing and migration responses are considered.

This paper has shown that it is both theoretically important and empirically relevant to consider the joint determination of migration and risk sharing. While the current focus has been migration, it is reasonable to think that many other decisions that households make may also be jointly determined with informal insurance. Additionally, an important open question is that of the determinants of the long run changes observed between the first wave of the VLS in 1975 and the second wave in 2001: what caused the large increase in temporary migration over this time period and how did this increase in temporary migration affect the long run development of India's village economies? Fruitful avenues for future research may be to examine the implications of the joint determination of informal risk sharing and investment or production decisions as well as examining the determinants of the long run changes observed in India's village economies.

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Figures and Tables

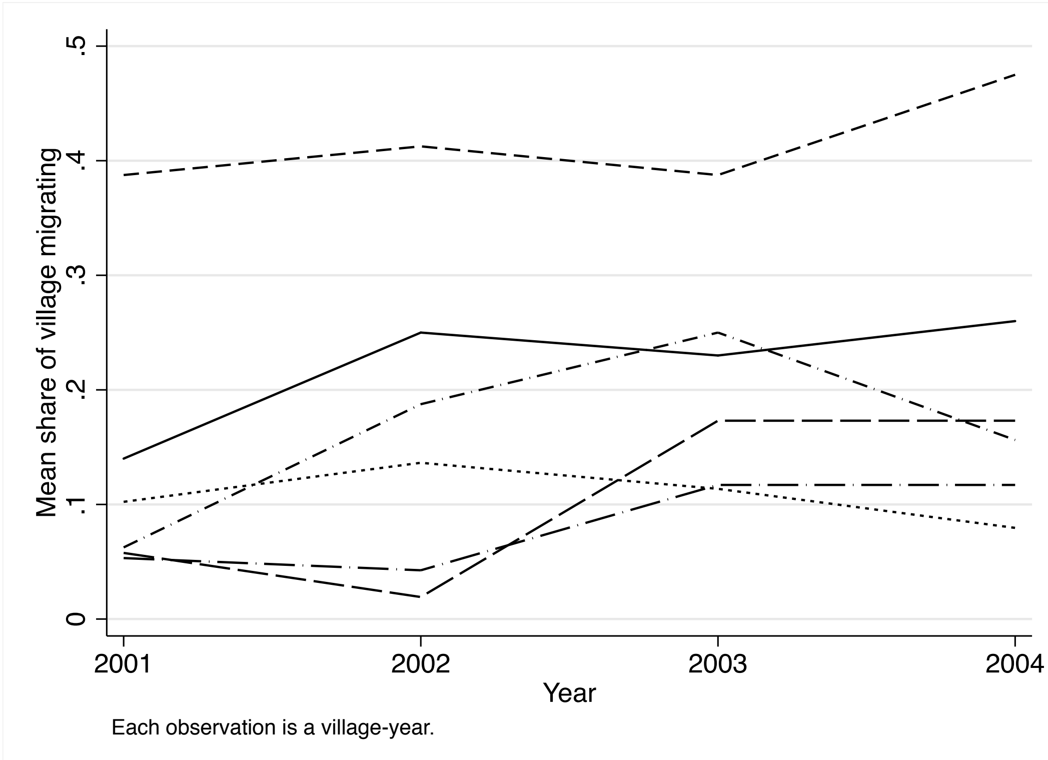


Figure 1: Migration varies over space and time: Temporary migration in the six ICRISAT villages over time.

Notes: The figure plots the share of households with a temporary migrant in each of the six ICRISAT villages by year.

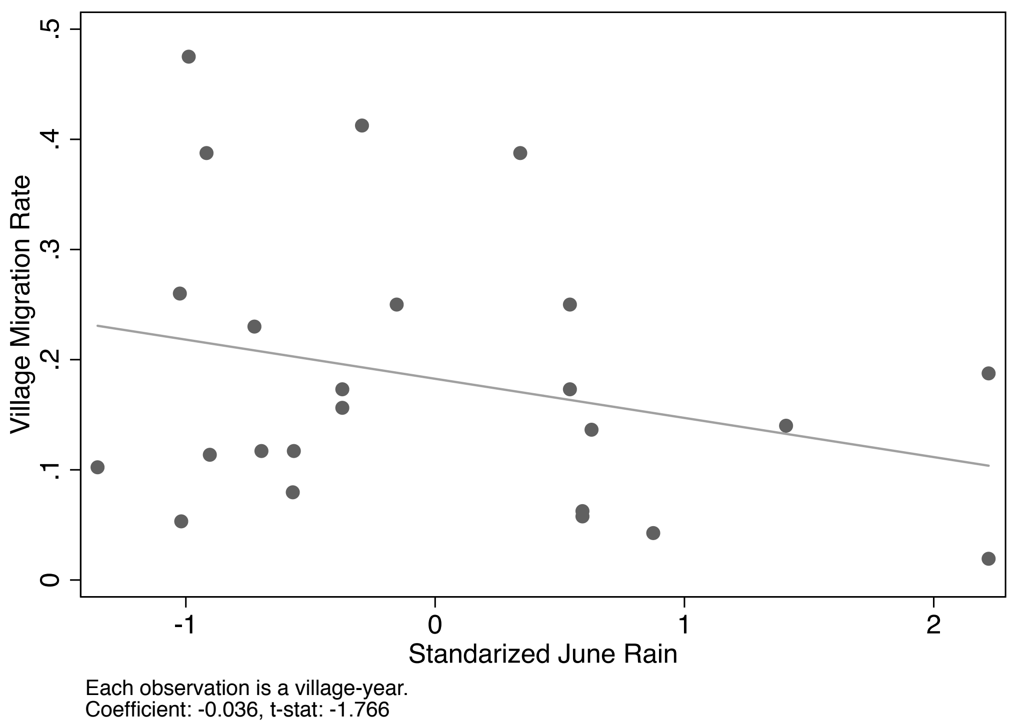


Figure 2: Verifying model assumptions: Temporary migration responds ex-post to income shocks.

Notes: The figure plots the relationship between the mean village migration rate and the standardized monsoon (June) rainfall in the six ICRISAT villages between 2001-2004. Monsoon rainfall is a strong predictor of crop income for the coming year. Migration decisions are made after the monsoon rainfall and respond to expected income shocks. The unit of observation is a village-year; there are 24 observations. A regression line is included in the figure.

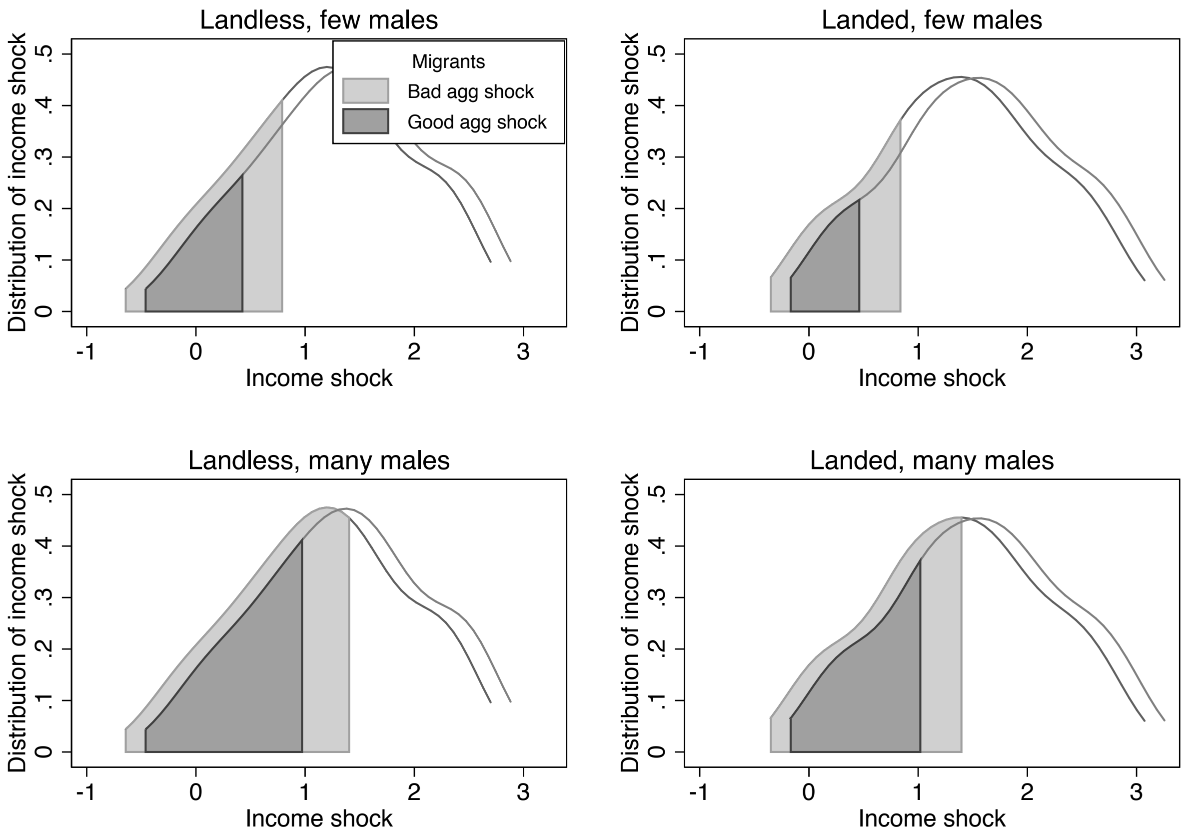


Figure 3: Structural estimation: Income distribution and selection into migration by population subgroup

Notes: The figure plots the migration and income distribution for each subgroup (males/land) for good and bad aggregate shocks. Computed from structural estimation results. The shaded area represents the agents who migrate in each period. Because the income process is discretized, I use the median income of migrants as the threshold to highlight the differences between aggregate and idiosyncratic shocks.

Table 1: Summary statistics

Mean/sd	(1) All	(2) Ever Migrate	(3) Never Migrate
Total income	22.64	23.45	22.12
	(18.23)	(17.57)	(18.63)
Non-migration income	21.46	18.64	23.24
	(22.64)	(22.08)	(22.82)
Migration income	2.38	6.19	0.00
	(6.10)	(8.55)	(0.00)
Total consumption	26.73	26.71	26.74
	(16.22)	(15.56)	(16.63)
Per capita consumption	6.78	6.25	7.11
	(4.24)	(4.43)	(4.09)
Owned land	4.81	4.39	5.08
	(5.57)	(5.85)	(5.37)
Household size	5.08	5.82	4.61
	(2.44)	(2.57)	(2.23)
Number adults	3.72	4.23	3.40
	(1.64)	(1.65)	(1.56)
Number adult males	1.91	2.23	1.72
	(1.08)	(1.08)	(1.03)
Number migrants		1.77	
		(0.96)	
Share household migrating		0.33	
		(0.19)	
Migration length (days)		192.98	
		(102.67)	
Number households	439	171	268

Notes: Summary statistics calculated from VLS2. All financial variables in '000s of rupees. Per capita consumption computed in adult equivalent terms. Migration variables computed only for years in which the household migrates.

Table 2: Test for perfect risk sharing

Dep. variable: Consumption	(1) b/se	(2) b/se
Income	0.070***	0.029
	(0.016)	(0.022)
Mean village migration *X* Income		0.234*
		(0.122)
Village-Year FE	Yes	Yes
Household FE	Yes	Yes
R-squared	0.627	0.629
Number observations	1443	1443

Notes: OLS regressions of log income on log consumption. Standard errors clustered at village-year level for all columns. VLS2 is ICRISAT data 2001-2004. Mean village migration interacts the average village level of temporary migration with individual income.

Table 3: Transfers are insurance

	In levels		In first difference	
Dep. variable: (Diff) Transfers	(1) b/se	(2) b/se	(3) b/se	(4) b/se
Total Income	-0.967***	-0.845***		
	(0.031)	(0.033)		
Stock of transfers		-0.261***		
		(0.024)		
D.Total Income			-0.971***	-0.736***
			(0.033)	(0.034)
D.Stock of transfers				-0.497***
				(0.033)
Village-Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	No	No
r2	0.729	0.753	0.534	0.650
N	1446	1236	919	824

Notes: Source: VLS2. Transfers are defined as the residal between income and consumption. Stock of transfers measures the combined value of transfers received, setting 2001 equal to zero.

Table 4: Change in household income and expenditure when migrate

Dep. variable:	(1) Income b/se	(2) Consumption b/se	(3) Δ Fin. Assets b/se	(4) Δ Phy. Assets b/se	(5) Expenditure b/se
Dummy if migrate	1451	602	404	339	1104
	(492)	(521)	(317)	(490)	(902)
Household FE	Yes	Yes	Yes	Yes	Yes
Mean dep. variable	5828	6856	-598	292	6247
R-squared	0.650	0.512	0.215	0.304	0.369
Number observations	1446	1449	1490	1490	1510
Number households	438	438	437	437	438

Notes: OLS regressions with standard errors clustered at village-year. Calculated from ICRISAT data 2001-2004. Change in financial assets is change in savings less change in debt. Change in physical assets is change in value of durables, farm equipment, and livestock. Change variables calculated 2002-2004. Expenditure is sum of columns 2-4, assigning predicted change in assets for year 2001. Mean dependent variable calculated over non-migrants.

Table 5: Goodness of fit of model to data, by village

	Village 1		Village 2		Village 3		Village 4		Village 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Mean of non-migrant income	8.201	7.848	5.220	5.912	5.001	5.229	5.026	5.163	5.075	5.322
Std dev non-migrant income	4.672	4.269	3.225	3.196	4.130	4.384	3.937	4.073	3.680	3.906
Mean of non-migrant income: own land	8.959	9.449	5.281	5.942	5.401	5.289	5.843	5.433	6.076	5.866
Mean of migrant income	6.796	6.596	5.028	4.942	6.696	6.922	5.832	5.579	5.605	5.496
Std dev migrant income	3.897	4.629	3.195	3.730	4.462	4.623	3.770	4.095	5.290	4.640
Mean migration rate	0.238	0.265	0.454	0.379	0.078	0.002	0.074	0.031	0.078	0.053
Mean migration rate: male hh	0.553	0.472	0.536	0.567	0.105	0.004	0.109	0.044	0.125	0.106
Correlation of consumption and income	0.215	0.217	0.240	0.236	0.154	0.208	0.325	0.308	0.108	0.129
Mean non-migrant consumption	8.378	7.691	5.303	5.464	5.159	5.138	5.137	5.116	5.129	5.294
Mean migrant consumption	6.227	6.602	4.928	5.494	4.823	4.392	4.435	4.626	4.967	5.299
J statistic		2.433		2.222		2.365		1.040		0.867
J statistic (p value)		0.296		0.329		0.307		0.594		0.648

Notes: Table reports how well the model matches the data by moment. All monetary values are 000's of rupees per adult equivalent in household.

Table 6: Structural point estimates (by village)

	A b/se	B b/se	C b/se	D b/se	E b/se	Average b/se
Village income						
Mean of village shock process	1.392	1.120	1.173	1.120	1.120	1.185
	(0.045)	(0.008)	(0.248)	(0.003)	(0.064)	(0.052)
Std. dev of village shock process	0.537	0.780	0.922	0.874	0.811	0.785
	(0.058)	(0.025)	(0.162)	(0.009)	(0.005)	(0.035)
Migration income						
Mean of migration income process	1.517	1.419	1.885	1.794	1.544	1.632
	(0.079)	(0.185)	(0.181)	(0.174)	(0.006)	(0.064)
Std. dev of migration income process	1.287	1.203	1.038	1.015	1.281	1.165
	(0.037)	(0.062)	(0.014)	(0.152)	(0.014)	(0.034)
Utility cost of migrating						
Utility cost of migrating	0.089	0.132	0.390	0.281	0.226	0.223
	(0.116)	(0.026)	(0.038)	(0.277)	(0.061)	(0.062)
Preference parameters						
Discount factor	0.659	0.567	0.546	0.528	0.614	0.583
	(0.010)	(0.039)	(0.203)	(0.183)	(0.020)	(0.055)
Heterogeneity parameters						
Scaling utility cost for male	-0.945	-0.884	-0.277	-0.134	-0.571	-0.562
	(0.337)	(0.119)	(0.108)	(0.187)	(0.047)	(0.084)
Scaling mean for land	0.746	0.012	0.023	0.137	0.262	0.236
	(0.186)	(0.026)	(0.113)	(0.131)	(0.016)	(0.051)
Coefficient of relative risk aversion	1.600	1.600	1.600	1.600	1.600	1.600
Scaling factor good aggregate shock	0.200	0.200	0.200	0.200	0.200	0.200
Share of income from migration	0.600	0.600	0.600	0.600	0.600	0.600

Notes: Table gives point estimates and standard errors from simulated method of moment estimation. Columns (1)-(5) yield village-specific estimates. Column (6) averages across villages (note: standard error for the average does not take into account covariance across village as this was not estimated). Three parameters are set exogenously: the coefficient of relative risk aversion, the share of household income from migration and the scaling effect of a good aggregate shock.

Table 7: Effect of migration on village income and income of migrants

	(1) Data	(2) Model
Income of Migrants		
Observed mean income	5.802	5.615
Mean income if stayed in village		2.856
Share of migrants with income gain		0.674
Village Income		
Observed mean income of non-migrants	5.837	5.785
Mean of untruncated village income distribution		5.357

Notes: Model column calculated using structural estimates. All monetary values are 000's of rupees per adult equivalent in household. Migration is endogenous: the agents with the lowest income realizations migrate. This causes the income distribution in the village to be left-truncated.

Table 8: Effect on risk sharing of reducing the cost of migration

	Whole sample		Only non-migrants	
	(1)	(2)	(3)	(4)
Risk sharing: corr(y, c)	No migration mean	With migration mean	No migration mean	With migration mean
Overall	0.144	0.224	0.150	0.231
Landless, few males	0.139	0.207	0.143	0.205
Landed, few males	0.127	0.214	0.129	0.215
Landless, many males	0.146	0.199	0.169	0.210
Landed, many males	0.124	0.202	0.138	0.207

Notes: Table compares risk sharing in an economy with the cost of migration very high so that noone migrates to the same economy with the cost of migration as estimated in the model. The risk sharing measure is the correlation between consumption and income. Columns 1 and 2 compute the statistic for the whole sample. Columns 3 and 4 compute the statistic only for households who don't migrate when they have the option: this keeps income constant. Risk sharing is crowded out by the increase in households' outside option with migration.

Table 9: Effect of reducing the cost of migration under different risk sharing regimes

	(1) Autarky	(2) Exogenous incomplete	(3) Endogenous incomplete
Migration rate			
Overall	0.353	0.315	0.143
Landless, few males	0.319	0.265	0.066
Landed, few males	0.227	0.166	0.046
Landless, many males	0.466	0.477	0.275
Landed, many males	0.399	0.353	0.186
Welfare gain relative to no migration			
Overall	1.132	1.070	0.959
Landless, few males	1.128	1.061	0.941
Landed, few males	1.093	1.040	0.945
Landless, many males	1.178	1.106	0.974
Landed, many males	1.131	1.072	0.976
Consumption equivalent gain relative to no migration			
Overall	0.240	0.170	-0.099
Landless, few males	0.216	0.137	-0.150
Landed, few males	0.166	0.094	-0.142
Landless, many males	0.326	0.262	-0.053
Landed, many males	0.253	0.185	-0.050

Notes: Table shows change in welfare with migration compared to no migration for whole sample and by subgroup. Endogenous incomplete markets is the limited commitment model. No risk sharing is autarky. Exogenous incomplete markets considers a Hugget (1993) economy where agents can buy and sell a risk-free asset.

Table 10: Effect of NREGA under different regimes

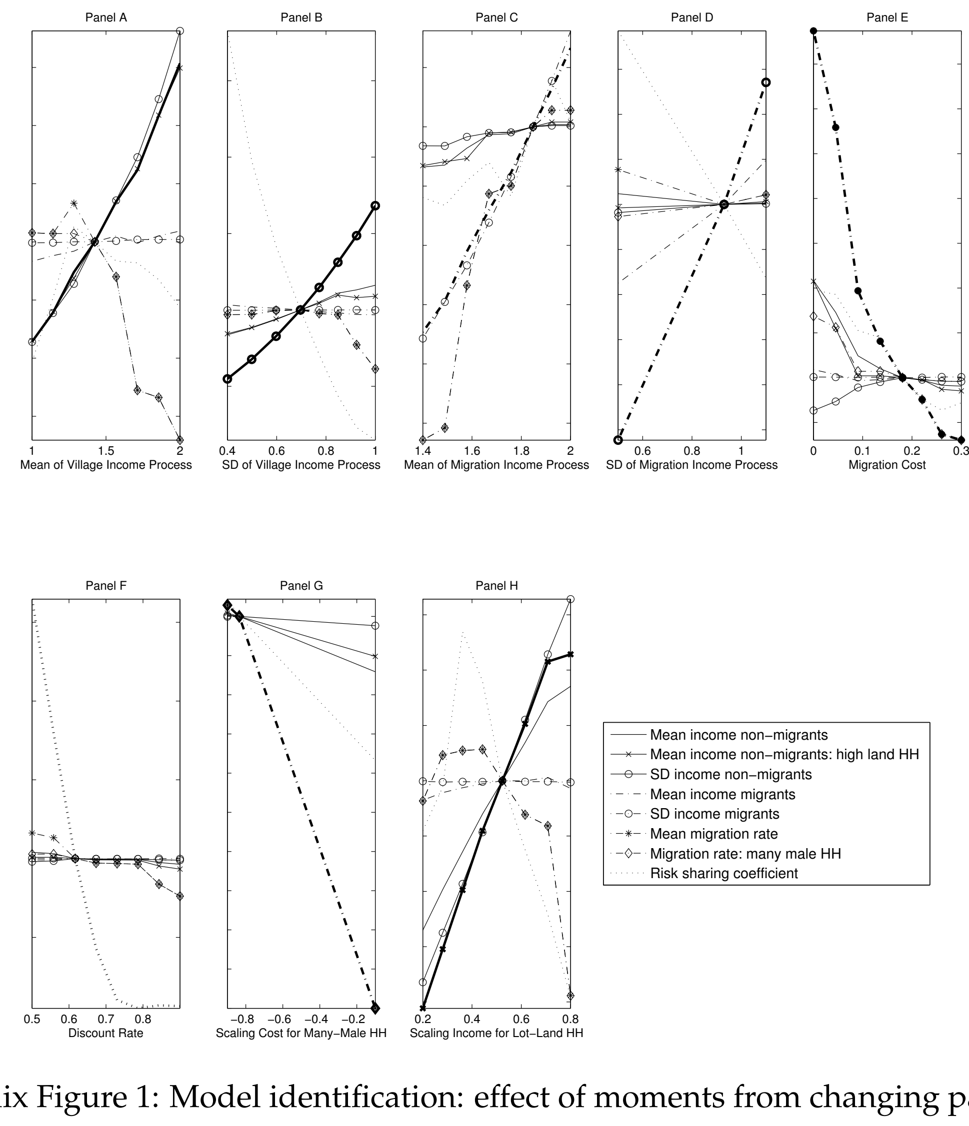
	Without migration			With migration		
	(1)	(2)	(3)	(4)	(5)	(6)
	Autarky	Exog	Endog	Autarky	Exog	Endog
Consumption equivalent gain with NREGA						
Overall	0.220	0.124	0.047	0.048	0.040	0.021
Landless, few males	0.242	0.136	0.051	0.056	0.049	0.026
Landless, many males	0.198	0.111	0.047	0.047	0.044	0.023
Landed, few males	0.242	0.136	0.045	0.049	0.037	0.020
Landed, many males	0.198	0.111	0.044	0.040	0.031	0.015
Correlation between income and consumption with NREGA relative to pre-NREGA						
Overall			1.448			1.172
Landless, few males			1.424			1.220
Landless, many males			1.475			1.204
Landed, few males			1.415			1.132
Landed, many males			1.478			1.133
Migration rate with NREGA relative to pre-NREGA						
Overall				0.895	0.903	0.862
Landless, few males				0.800	0.867	0.749
Landless, many males				0.750	0.854	0.801
Landed, few males				1.000	0.947	0.933
Landed, many males				1.000	0.946	0.965

Notes: NREGA policy enacts an income floor in the village. The policy is computed allowing for migration and not allowing for migration. Endog. is limited commitment. Exog. is exogenously incomplete markets. Autarky is no risk-sharing.

NOT FOR PUBLICATION

Appendices

A Appendix Tables and Figures



Appendix Figure 1: Model identification: effect of moments from changing parameters

Notes: This figure shows graphically how the moments in the model change as a function of the parameters. For each plot, I scale the moments so that they are equal for the initial parameter value. The x axis is the value of the parameter and the y axis yields the normalized value of the moment. For each plot, I scale the moments so that they are equal for the initial parameter value.

Appendix Table 1: Characteristics of migrant households

Dependent variable: Ever migrate	(1) b/se	(2) b/se
Number Males	0.197***	0.203***
	(0.036)	(0.034)
Land Owned	-0.004	0.002
	(0.006)	(0.006)
LandXMale	-0.010**	-0.011***
	(0.004)	(0.004)
HHsize	0.035***	0.038***
	(0.010)	(0.010)
Village FE	No	Yes
R-squared	0.110	0.213
Number observations	446	446

Notes: Dependent variable is a dummy for whether a household participates at least once in the temporary migrant labor market between 2001 and 2004.

Appendix Table 2: Returns in the village and migrant labor market

	Village Labor Market			Migrant Labor Market			Decision to Migrate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Male	Female	Both	Male	Female	Both	Male	Female	Both
Dep. variable: Log Wage	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Age	0.001*	-0.000	0.001**	0.004	-0.004	0.002	-0.005***	-0.003***	-0.004***
	0.001	0.000	0.000	0.004	0.007	0.003	0.001	0.001	0.001
Years of education	0.010***	0.003	0.007***	0.034**	0.108**	0.038***	0.021***	-0.000	0.019***
	0.003	0.004	0.002	0.015	0.049	0.013	0.004	0.005	0.003
Years of education missing	-0.007	0.016	0.003	0.151	0.242	0.141	0.114***	0.069**	0.122***
	0.028	0.020	0.017	0.145	0.232	0.119	0.032	0.029	0.022
Yrs experience in sector	0.038***	-0.005	0.015**	0.020	0.066	0.025			
	0.010	0.007	0.006	0.050	0.078	0.042			
Male			0.683***			0.214**			0.199***
			0.012			0.085			0.015
Vill-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1121	1172	2293	416	154	570	1448	1260	2708
r2	0.172	0.277	0.690	0.284	0.330	0.295	0.309	0.160	0.261

Notes: Sample is VLS2. Sectoral experience omitted in migration decision specification to avoid mechanical correlation and bad control problem.

Appendix Table 3: Effect of aggregate shocks on income

Dep. variable: Log Income	(1) b/se	(2) b/se	(3) b/se	(4) b/se
Number days monsoon late	-0.009***			
	(0.001)			
Bottom 10% shock		-0.923***		
		(0.103)		
Bottom 20% shock			-0.231***	
			(0.064)	
Bottom 50% shock				-0.104**
				(0.050)
Household FE	Yes	No	No	No
Long run prob. shock		0.14	0.28	0.49
R-squared	0.606	0.625	0.591	0.586
Number observations	931	931	931	931

Notes: OLS regressions using VLS1 (1975-1984). Rainfall shocks computed using the distribution of rainfall 1900-2008 from the University of Delaware precipitation database, and these thresholds applied to the ICRISAT colllected rainfall for 1975-1984. Monsoon start date is computed as the first day with more than 20 mm of rain after June 1, following Rosenzweig and Binswanger (1993).

Appendix Table 4: No evidence of income persistence

Dep. variable: Log Income	(1) OLS b/se	(2) Arellano-Bond estimator b/se
Lagged income	-0.044	0.081
	(0.036)	(0.077)
I_hh	0.000	0.000
	(.)	(.)
Number observations	719	719

Notes: Regressions using VLS1 (1975-1984). Household fixed effects included in both specifications. Column (1) estimates the system by OLS. Column (2) estimates the system by Arellano-Bond system GMM to consistently estimate lagged effect in presence of fixed effect.

Appendix Table 5: Robustness: Structural point estimates (by village)

	nhh = 4, $\rho = 0$				nhh = 20, $\rho = 0$				nhh = 4, $\rho = 0.1$				nhh = 20, $\rho = 0.1$			
	$\gamma = 1.4$	$\gamma = 1.6$	$\gamma = 2$	$\gamma = 2.5$	$\gamma = 1.4$	$\gamma = 1.6$	$\gamma = 2$	$\gamma = 2.5$	$\gamma = 1.4$	$\gamma = 1.6$	$\gamma = 2$	$\gamma = 2.5$	$\gamma = 1.4$	$\gamma = 1.6$	$\gamma = 2$	$\gamma = 2.5$
	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
Village 1																
Beta	0.569	0.644	0.458	0.476	0.583	0.659	0.563	0.422	0.694	0.444	0.458	0.503	0.708	0.688	0.563	0.601
J stat	32.208	2.725	4.884	6.353	5.892	2.424	2.800	7.393	3.275	14.171	8.138	12.238	9.307	1.663	2.086	7.003
Village 2																
Beta	0.645	0.659	0.497	0.601	0.645	0.567	0.458	0.422	0.507	0.684	0.684	0.601	0.684	0.614	0.578	0.422
J stat	2.465	3.594	38.196	3.547	3.326	2.222	4.851	3.804	38.182	2.091	10.467	2.903	8.886	1.492	4.070	5.764
Village 3																
Beta	0.645	0.625	0.625	0.625	0.583	0.546	0.472	0.491	0.819	0.871	0.645	0.635	0.708	0.663	0.812	0.746
J stat	0.546	1.395	1.840	2.176	2.430	2.365	3.806	1.656	3.700	2.884	0.482	6.017	1.015	0.939	8.526	3.745
Village 4																
Beta	0.658	0.542	0.497	0.625	0.520	0.528	0.562	0.491	0.569	0.573	0.495	0.562	0.708	0.458	0.760	0.491
J stat	2.058	2.708	1.667	3.679	2.459	1.040	2.155	1.880	3.143	2.417	2.875	4.811	4.726	2.661	10.927	1.621
Village 5																
Beta	0.614	0.684	0.625	0.500	0.583	0.614	0.453	0.559	0.835	0.809	0.625	0.562	0.708	0.583	0.528	0.625
J stat	1.483	5.936	2.499	3.070	6.468	0.867	1.933	3.401	6.296	5.734	2.034	4.310	2.956	4.754	2.469	5.096
Average																
Beta	0.626	0.631	0.540	0.565	0.583	0.583	0.502	0.477	0.685	0.676	0.581	0.573	0.703	0.601	0.648	0.577
J stat	7.752	3.272	9.817	3.765	4.115	1.784	3.109	3.627	10.919	5.459	4.799	6.056	5.378	2.302	5.616	4.646

Notes: Table gives point estimates of beta and the critical value from simulated method of moment estimation.

B Theoretical appendix

B.1 Proof of Proposition 4.1

For a given discount factor β and relative risk aversion γ, there exists a lower bound on the size of the income shock $\underline{\alpha}(\beta,\gamma)$ and an upper bound $\overline{\alpha}(\beta,\gamma)$such that consumption α^c is given by

$$\alpha^c = \begin{cases} \alpha^\Omega & \text{if } \alpha^\Omega < \underline{\alpha}(\beta,\gamma) \ \ \text{(Autarky)} \\ \alpha^c(\alpha^\Omega,\beta,\gamma) & \text{if } \alpha^\Omega \in [\underline{\alpha}(\beta,\gamma),\overline{\alpha}(\beta,\gamma)] \ \ \text{(Imperfect risk sharing)} \\ 0.5 & \text{if } \alpha^\Omega > \overline{\alpha}(\beta,\gamma) \ \ \text{(Perfect risk sharing)} \end{cases}$$

Further, the partial derivatives of α^c with respect to its arguments are signed as following: $\alpha^c_1(\alpha^\Omega,\beta,\gamma) < 0, \alpha^c_2(\alpha^\Omega,\beta,\gamma) < 0$, and $\alpha^c_3(\alpha^\Omega,\beta,\gamma) > 0$.

Proof:

The participation constraint for the rich agent is given by:

$$u(\alpha^c Y) + \beta u((1-\alpha^c)Y) = u(\alpha^\Omega Y) + \beta u((1-\alpha^\Omega)Y)$$

Assuming CRRA utility, this simplifies to:

$$(\alpha^c)^{1-\sigma} + \beta(1-\alpha^c)^{1-\sigma} = (\alpha^\Omega)^{1-\sigma} + \beta(1-\alpha^\Omega)^{1-\sigma}$$

The RHS of the above expression is a concave function of α^Ω. Taking the derivative with respect to α^Ω and rearranging yields that $\underline{\alpha}(\beta,\gamma) = \frac{1}{1+\beta^{1/\gamma}}$. The upper bound where full risk sharing becomes optimal is defined as the $\overline{\alpha}(\beta,\gamma)$ that solves $(1+\beta)0.5^{1-\gamma} = \overline{\alpha}^{1-\gamma} + \beta(1-\overline{\alpha})^{1-\gamma}$. Then, by the implicit function theorem, if $\alpha^\Omega \in [\underline{\alpha},\overline{\alpha}]$, $\alpha^c = f(\alpha^\Omega,\beta,\gamma)$ where $\frac{\partial \alpha^c}{\partial \alpha^\Omega} < 0$ (risk sharing is better, meaning that consumption is closer to 0.5, if income is riskier), $\frac{\partial \alpha^c}{\partial \beta} < 0$ (risk sharing is better if agents are more patient), and $\frac{\partial \alpha^c}{\partial \gamma} > 0$ (risk sharing is worse if agents are more risk averse).

C Computational appendix

This computational appendix discusses the extension to the N household case and the approximation errors with estimating the model as if there were only two households; the algorithm to solve the limited commitment model; and the algorithm to find the transition matrices that satisfy the market clearing conditons.

C.1 Extending the model from 2 to N agents

The model presented in Section 2 was for two households. Here I show how to extend the model to N agents and then discuss the aggregation issues from solving a N agent games as if there were two households in the village.

C.1.1 Model with N agents

The model easily extends from 2 to N agents. Denote by H the numeraire household in the economy. We can write the model as:

$$
\begin{aligned}
V^H(U_s^1, ..., U_s^{H-1}; s) = & \max_{\{c^i_{sjq}\}_{\forall i}; \{U^i_{jqr}\}_{\forall i \neq H}} \sum_j \sum_q \pi_j \pi_q \left\{ u(c^H_{sjq}) - \mathbb{I}^H_j d + \beta \sum_r \pi_{sr} V^H(U^1_{qjr}, ..., U^{H-1}_{qjr}; r) \right\} \\
\text{PK: } & \sum_{i \neq H} \lambda^i \left[\sum_j \sum_q \pi_j \pi_q \left(u(c^i_{sjq}) - \mathbb{I}^i_j d + \beta \sum_r \pi_{sr} U^i_{jqr} \right) - U^i_s \right] \\
\text{Ex ante IC: } & \sum_{i \neq H} \sum_j \sum_q \sum_r \pi_j \pi_q \lambda_i \beta \pi_{sr} \phi^i_{jqr} \left[U^i_{jqr} - \Omega^i_r \right] \\
\text{Ex post IC: } & \sum_{i \neq H} \sum_j \sum_q \pi_j \pi_q \lambda^i \alpha^i_{sjq} \left[u(c^i_{sjq}) - \mathbb{I}^i_j d + \beta \sum_r \pi_{sr} U^i_{jqr} - \hat{\Omega}^i_{sjr} \right] \\
\text{Ex ante IC (H) : } & \sum_j \sum_q \sum_r \pi_j \pi_q \beta \pi_{sr} \phi^H_{jqr} \left[V(U^1_{jqr}, ..., U^{H-1}_{jqr}; r) - \Omega^H_r \right] \\
\text{Ex post IC (H): } & \sum_j \sum_q \pi_j \pi_q \alpha^H_{sjq} \left[u(c^H_{sjq}) - \mathbb{I}^H_j d + \beta \sum_r \pi_{sr} V(U^1_{jqr}, ..., U^{H-1}_{jqr}; r) - \hat{\Omega}^H_{sjr} \right] \\
\text{Budget constraint: } & \sum_j \sum_q \pi_j \pi_q \gamma_{jq} \left[\sum_i c^i_{sjq} - \sum_i e^i_{sjq} \right]
\end{aligned}
$$

The first order conditions yield:

$$
\begin{aligned}
\frac{\partial}{\partial c^H_{sjq}} &: \ \pi_j \pi_q u'(c^H_{sjq}) + \pi_j \pi_q \alpha^H_{sjq} u'(c^H_{sjq}) = -\pi_j \pi_q \gamma_{jq} \\
\frac{\partial}{\partial c^i_{sjq}} &: \ \lambda^i \pi_j \pi_q u'(c^i_{sjq}) + \pi_j \pi_q \alpha^i_{sjq} u'(c^H_{sjq}) = -\pi_j \pi_q \gamma_{jq} \\
\frac{\partial}{\partial U^i_{jqr}} &: \ \pi_j \pi_q \beta \pi_{sr} V^H_i(U^1_{jqr}, .., U^{H-1}_{jqr}; r) + \lambda^i \pi_j \pi_q \beta \pi_{sr} + \pi_j \pi_q \beta \pi_{sr} \phi^i_{jqr} + \pi_j \pi_q \lambda^i \alpha^i_{sjq} \beta \pi_{s}
\end{aligned}
$$

$$
\text{Envelope : } \ V^H_i(U^1_s, ..., U^{H-1}_s; s) = -\lambda_i
$$

Rearranging the FOC yields:

$$\frac{u'(c^H_{sjq})}{u'(c^i_{sjq})} = \lambda^i \frac{1+\alpha^i_{sjq}}{1+\alpha^H_{sjq}} \tag{1}$$

$$V^H_i(U^1_{jqr},..,U^{H-1}_{jqr};r) = -\lambda^i \frac{(1+\alpha^i_{sjq}+\phi^i_{jqr})}{(1+\alpha^H_{sjq}+\phi^H_{jqr})} \tag{2}$$

$$V^H_i(U^1_s,...,U^{H-1}_s;s) = -\lambda_i \tag{3}$$

C.1.2 Aggregating to a 'rest of village' household

It would be computationally difficult to keep track of N agents in the optimization procedure because it would be necessary to track each additional household's relative pareto weight and income realization. Instead, I follow Ligon, Thomas and Worrall (2002) and most other empirical applications of the limited commitment model (Laczo (2015)) and construct an aggregated "rest of the village" household. To see this, consider the set of first order conditions that would result from a N person game, where the relative pareto weight is with respect to household H

$$\frac{u'(c^H_{sjq})}{u'(c^i_{sjq})} = \lambda^i \frac{1+\alpha^i_{sjq}}{1+\alpha^H_{sjq}}, \quad \forall i \neq H$$

Then, by CRRA utility

$$\frac{c^i}{c^H} = \left(\lambda^i \frac{1+\alpha^i_{sjq}}{1+\alpha^H_{sjq}}\right)^{\frac{1}{\sigma}}$$

And, we can sum over all $i \neq H$

$$\frac{\sum_{i\neq H} c^i}{c^H} = \sum_{i\neq H} \left(\lambda^i \frac{1+\alpha^i_{sjq}}{1+\alpha^H_{sjq}}\right)^{\frac{1}{\sigma}}$$

Define the average member of the village, relative to agent H, as $c^{-H} = \frac{1}{N-1}\sum_{i\neq H} c^i$.

$$\frac{c_{sjq}^{-H}}{c_{sjq}^{H}} = \frac{1}{N-1}\sum_{i \neq H}\left(\lambda^{i}\frac{1+\alpha_{sjq}^{i}}{1+\alpha_{sjq}^{H}}\right)^{\frac{1}{\sigma}}$$

Then, let $\lambda^{-H} = \frac{1}{N-1}\sum_{i\neq H}\lambda^{-i}$, and $\alpha^{-H} = \frac{1}{N-1}\sum_{i\neq H}\alpha^{-i}$:

$$\left(\frac{c_{sjq}^{-H}}{c_{sjq}^{H}}\right)^{\sigma} = \lambda^{-H}\frac{1+\alpha_{sjq}^{-H}}{1+\alpha_{sjq}^{H}}$$

$$\frac{u'(c_{sjq}^{H})}{u'(c_{sjq}^{-H})} = \lambda^{-H}\frac{1+\alpha_{sjq}^{-H}}{1+\alpha_{sjq}^{H}}$$

That is, the ratio of marginal utilities of the average member of the village excluding household H and household H can be expressed in terms of the relative pareto weight and the ex post constraints of the rest of the village.

Solving the model with the 2 household approximation assumes that the rest of the village is sharing risk perfectly with each other, and considers imperfect risk sharing between household i and the rest of the village. However, this assumption is not directly used when simulating the economy. Rather, I examine incentive constraints for each household one at a time, and then undertake an iterative process to ensure the economy-wide budget constraint is satisfied.

C.1.3 Accuracy of the discrete approximation

It is possible to check the accuracy of the approximation method against an alternative method of assuming that there are a continuum of agents and solving the limited commitment model and comparing the simulated distributions of consumption. The following section does this. I do this for the case of the standard limited commitment model. It is necessary to shut down aggregate shocks to solve the continuum model because of the standard problem that the total resources will be an infinitely-dimensioned object. I use the algorithm for the continuum case outlined in Krueger and Perri (2010). Table 6 compares the two solution methods, solved for both the continuum and the discrete case. The number of households represents how many households are averaged to construct the "rest of the village"

Appendix Table 6: Comparison of discrete approximation to continuum

	Continuum	Discrete			
	(1)	(2)	(3)	(4)	(5)
		4 HH	10 HH	30 HH	50 HH
Mean income	1.500	1.500	1.500	1.500	1.500
Mean consumption	1.500	1.500	1.500	1.500	1.500
Min consumption	1.073	1.099	1.099	1.099	1.099
Max consumption	1.765	1.807	1.790	1.694	1.631
Standard deviation consumption	0.160	0.315	0.301	0.222	0.163
Correlation income, consumption	0.808	0.976	0.964	0.876	0.806
Risk sharing beta	0.324	0.767	0.726	0.486	0.328

Notes: Table compares the limited commitment solution calculated two different methods.

household. The correlation between the solution found in the continuum and discrete case is high.

C.2 Algorithm to solve the limited commitment problem

This section documents algorithm to find the state-specific ex-ante intervals for the pareto weight $[\underline{\lambda}_s, \overline{\lambda}_s] \forall s$, the ex-post intervals for the pareto weights $[\hat{\underline{\lambda}}_{sqj}, \hat{\overline{\lambda}}_{sqj}], \forall s, \forall q, \forall j$ and the migration rule $\mathbb{I}(s, \lambda)$.

The algorithm is solved in two steps:

1. Solve the limited commitment algorithm for 2 households (household A and the "rest of the village" household[39]) to find the ex-ante intervals $[\underline{\lambda}_s, \overline{\lambda}_s] \forall s$, and the ex-post intervals $[\hat{\underline{\lambda}}_{sqj}, \hat{\overline{\lambda}}_{sqj}], \forall s, \forall q, \forall j$ and the migration rule $\mathbb{I}(s, \lambda)$. In this step, the fixed point of the migration decision (which determines the total resources available to the network) is found.

2. Once the fixed point of the problem is found, use the lower bounds of the computed ex ante and ex-post intervals to compute a transition matrix between ex ante and ex post states and the invariant distribution over income and earnings. The pareto weights of constrained agents are pinned down by the lower bound of the interval. The pareto weights for unconstrained agents have to satisfy the first order constraint. In order to satisfy the economy-wide budget constraint, the pareto weights of unconstrained agents are rescaled by state-specific factors β_s such that all agents have their participation constraint satisfied. In this step, the values of β_s such that market clearing occurs are found for each value of the state.

The model presented in the text followed the notation of Ligon et al. (2002) and presented the problem in terms of a social planner's value function where the state variable was the expected utility for the household. When computing the model it is more straightforward to work directly with a value function for each agent; as Marcet and Marimon (2011) have shown the two formulations of the problem are equivalent.

C.2.1 Step 1: Find the pareto intervals

Define the following, all computed recursively:

[39] I use $N = 20$ in the estimation. Appendix Table 5 shows robustness over the value of N.

- The ex-ante participation constraint

$$\Omega^i_{\text{ex-ante}}(s) = \max\{u(e^i(s)), \mathrm{E}u(m^i(q)) - d\} + \beta \mathrm{E}\Omega^i_{\text{ex-ante}}(s')$$

- The ex-post participation constraint

$$\Omega^i_{\text{ex-post}}(s, q, \mathbb{I}^i) = \mathbb{I}^i u(m^i(q)) + (1 - \mathbb{I}^i)u(e^i(s)) + \beta \mathrm{E}\Omega^i_{\text{ex-ante}}(s')$$

- First-best risk-sharing (no migration)

$$V^i_{\text{first-best}}(s) = u(\frac{e^A(s) + e^B(s)}{2}) + V^i_{\text{first-best}}(s)$$

1. Construct an ex-ante grid over the state of the world and the pareto weight (s, λ) and an ex-post grid over the village state of the world, the ex post pareto weight, the migration state of the world, and the migration outcome $(s, \hat{\lambda}, q, j)$.

2. Construct an initial guess for the value of ex-ante utility for agent A, $V_0^A(s, \lambda)$ and the utility of agent B, $V_0^B(s, \lambda)$. A good initial guess is to take the max of perfect risk sharing and autarky.

3. Guess an initial migration rule, $\mathbb{I}_0(s, \lambda)$.

4. Compute the total resources for the economy, taking into account the expected level of migration.

5. For each ex-post grid point (s_i, λ_j, q_k, j).

   (a) Construct the sub-value function if agent A does not migrate ($j = 0$):

   $$\hat{V}_0^A(s_i, \lambda_j, q_k, 0) = u(c^A(s_i, \lambda_j)) + \beta \sum_r \pi_{sr} V_0^A(r, \lambda_j)$$

   (b) Construct the sub-value function if agent A migrates ($j = 1$):

   $$\hat{V}_0^A(s_i, \lambda_j, q_k, 1) = u(c^A(s_i, \lambda_j, q_k)) - \mathbb{I}d + \beta \sum_r \pi_{sr} V_0^A(r, \lambda_j)$$

   (c) Construct the same values for agent B. Note we only consider the migration decision for agent A because B is the rest-of-village household; the average migration rate will be captured through the total resources available to the network.

$$\hat{V}^B_0(s_i, \lambda_j, q_k, 0) = u(c^B(s_i, \lambda_j)) + \beta \sum_r \pi_{sr} V^B_0(r, \lambda_j)$$
$$\hat{V}^B_0(s_i, \lambda_j, q_k, 1) = u(c^B(s_i, \lambda_j, q_k)) + \beta \sum_r \pi_{sr} V^B_0(r, \lambda_j)$$

(d) For each of the q migration outcomes find the intervals that satisfy both agents' ex-post participation constraints if A migrates:

$$\underline{\hat{\lambda}}_{s,q,1} := \hat{V}^A_0(\lambda^*, q, 1) = \hat{\Omega}^A(s, q, \mathbb{I})$$

$$\overline{\hat{\lambda}}_{s,q,1} := \hat{V}^B_0(\lambda^*, q, 1) = \hat{\Omega}^B(s, q)$$

(e) Find the intervals that satisfy both agents' ex-post participation constraints if A does not migrate):

$$\underline{\hat{\lambda}}_{s,q,0} := \hat{V}^A_0(\lambda^*, 0) = \hat{\Omega}^A(s)$$

$$\overline{\hat{\lambda}}_{s,q,0} := \hat{V}^B_0(\lambda^*, 0) = \hat{\Omega}^B(s)$$

(f) For values of $\hat{\lambda} \notin [\underline{\hat{\lambda}}_{sqj}, \overline{\hat{\lambda}}_{sqj}], \forall s, \forall q, \forall j$ replace the value function with the value of ex-post autarky for *both* agent A and B.

6. For each ex-ante grid point (s_i, λ_j).

(a) Construct the total expected utility of agent A and B if agent A migrates:

$$\hat{V}(s_i, \lambda_j, 1) = \sum_k \pi^m_{q_k} \hat{V}^A_0(s_i, \lambda_j, q_k, 1) + \sum_k \pi^m_{q_k} \hat{V}^B_0(s_i, \lambda_j, q_k, 1)$$

(b) Construct the total expected utility of agent A and B if agent A does not migrate:[40]

$$\hat{V}(s_i, \lambda_j, 0) = \sum_k \pi^m_{q_k} \hat{V}^A_0(s_i, \lambda_j, q_k, 0) + \sum_k \pi^m_{q_k} \hat{V}^B_0(s_i, \lambda_j, q_k, 0)$$

[40]The expectation does not depend on value of q, but it is defined over the same grid for completeness.

(c) Now construct the migration vector. We use a smoothed version of the discrete choice with smoothing parameter β. As $\beta \to 0$ this collapses to the discrete choice rule:

$$\mathbb{I}_1(s_i, \lambda_j) = \frac{\exp(\hat{V}(s_i, \lambda_j, 1)/\beta)}{\exp(\hat{V}(s_i, \lambda_j, 0)/\beta) + \exp(\hat{V}(s_i, \lambda_j, 1)/\beta)}$$

(d) Update the ex-ante value functions

$$V_1^A(s_i, \lambda_j) = \mathbb{I}(s_i, \lambda_j) \sum_k \pi_{q_k}^m \hat{V}_0^A(s_i, \lambda_j, q_k, 1) + (1 - \mathbb{I}(s_i, \lambda_j)) \sum_k \pi_{q_k}^m \hat{V}_0^A(s_i, \lambda_j, q_k, 0)$$
$$V_1^B(s_i, \lambda_j) = \mathbb{I}(s_i, \lambda_j) \sum_k \pi_{q_k}^m \hat{V}_0^B(s_i, \lambda_j, q_k, 1) + (1 - \mathbb{I}(s_i, \lambda_j)) \sum_k \pi_{q_k}^m \hat{V}_0^B(s_i, \lambda_j, q_k, 0)$$

(e) Find the ex-ante interval $[\underline{\lambda}_s, \overline{\lambda}_s]$ that satisfy both agents' ex-ante participation constraint:

$$\underline{\lambda}_s := V_1^A(\lambda^*; s) = \Omega^A(s)$$
$$\overline{\lambda}_s := V_1^B(\lambda^*; s) = \Omega^B(s)$$

(f) For values of $\lambda \notin [\underline{\lambda}_s, \overline{\lambda}_s]$, replace the exante-value function with the value of ex-ante autarky for *both* agent A and B.

7. Compare $\{V_1^A(s, \lambda), V_1^B(s, \lambda)\}$ with $\{V_0^A(s, \lambda), V_0^B(s, \lambda)\}$. Repeat Steps 5 to 6 until convergence.

8. Compare $\mathbb{I}_1(s, \lambda)$ with $\mathbb{I}_0(s, \lambda)$. Repeat Steps 4 to 6 until convergence.

C.2.2 Step 2: Find the transition matrices

Once the ex ante intervals $[\underline{\lambda}_s, \overline{\lambda}_s] \forall s$, the ex-post intervals $[\hat{\underline{\lambda}}_{sqj}, \hat{\overline{\lambda}}_{sqj}], \forall s, \forall q, \forall j$ and the migration rule $\mathbb{I}(s, \lambda)$ have been constructed, this step finds the transition matrices that are used to simulate the economy. Additionally we find state-dependent ex post scalars β_s to ensure that the economy-wide budget constraint (that total consumption is equal to total earnings, including earnings from migration) is satisfied for each point in time.

1. Start with a guess for each β_s e.g. $\beta_s = 1, \forall s$

2. For each grid point on the ex post grid (s_i, λ_j, q_k, j)

(a) Compute the updating rule for the pareto weight. This will be the lower bound of the interval if the participation constraint is binding. If the participation constraint is not binding this will be the current value of the pareto weight, multiplied by an economy-wide scalar.

$$\hat{\lambda}(s_i, \lambda_j, q_k, j) = \max[\underline{\lambda}_{sqj}, \beta_s \lambda_j]$$

(b) Find the two neighboring points λ_l, λ_h on the grid for λ such that $\hat{\lambda}(s_i, \lambda_j, q_k, j) = x\lambda_l + (1-x)\lambda_h$

(c) Define a transition matrix between ex-ante and ex-post within the period

$$Q_{\text{ex-ante,ex-post}} : (s \times \lambda) \times (s \times \lambda \times q \times j) \to [0, 1]$$

as

$$Q_{\text{ex-ante,ex-post}}((s_i, \lambda_j), (s_i, \lambda_j, q_k, j)) = \begin{cases} \pi^m(q_k)\pi^{\mathbb{I}}(j)x & \text{if } \hat{\lambda} = \lambda_l \\ \pi^m(q_k)\pi^{\mathbb{I}}(j)(1-x) & \text{if } \hat{\lambda} = \lambda_h \\ 0 & \text{otherwise} \end{cases}$$

$$\lambda_1(s_i, \lambda_j, q_k, j) = \max[\underline{\lambda}_{s_i}, \hat{\lambda}(s_i, \lambda_j, q_k, j)]$$

(d) Find the two neighboring points λ_l, λ_h on the grid for λ such that $\lambda_1(s_i, \lambda_j, q_k, j) = x\lambda_l + (1-x)\lambda_h$

(e) Define a transition matrix between the current ex-post and tomorrow's ex-ante state:

$$Q_{\text{ex-post,ex-ante}} : (s \times \hat{\lambda} \times q \times j) \times (s' \times \lambda') \to [0, 1]$$

as

$$Q_{\text{ex-post,ex-ante}}((s, \hat{\lambda}, q, j), (s', \lambda')) = \begin{cases} \pi^e(s_i)x & \text{if } \lambda' = \lambda_l \\ \pi^e(s_i)(1-x) & \text{if } \lambda' = \lambda_h \\ 0 & \text{otherwise} \end{cases}$$

3. Construct the full transition matrix Q. This matrix has dimension $(N_S, N_\lambda) \times (N_S, N_\lambda)$

$$Q : (s, \lambda) \times (r \times \lambda') \to [0, 1] = Q_{\text{ex-ante,ex-post}}((s, \lambda), (s, \hat{\lambda}, q, j)) \times Q_{\text{ex-post,ex-ante}}((s, \hat{\lambda}, q, j), (r, \lambda'))$$

4. Then solve the matrix equation

$$\phi = Q^T \phi$$

where $\phi(s, \lambda)$ gives the steady state probability of being in state (s, λ).

5. Using $\phi(s, \lambda)$ compute the steady state ex post probability of being in state $\hat{\phi}(s, \hat{\lambda}, q, j) = Q^T_{\text{ex-ante,ex-post}} \phi(s, \lambda)$

6. Compute the excess demand function

$$d(\beta_s) = \sum_{(s,\hat{\lambda},q,j) \in (N_S, N_\lambda, N_q, N_j)} \left(c(s, \hat{\lambda}, q, j) - e(s, \hat{\lambda}, q, j) - m(s, \hat{\lambda}, q, j) \right) \hat{\phi}(s, \hat{\lambda}, q, j)$$

7. Repeat Steps 2 to 6 and use a Newton procedure to find β_s such that $d(\beta_s) = 0$ so that market clearing is satisfied.