Migration and Consumption Insurance in Bangladesh *

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Abstract

We investigate the relationship between seasonal migration and informal risk sharing in rural Bangladesh. We use data from a randomized controlled trial which provided incentives for households to migrate (Bryan et al., 2014). Using this experimental variation, we first provide evidence of the effect of decreasing migration costs on endogenous risk sharing in the village. We then investigate the mechanisms of this effect. We undertake a semi-parametric analysis of the source of income shocks, source of insurance and measurement error. Next, we characterize a dynamic model of migration and endogenous risk sharing, incorporating investment in learning about migration possibilities. Estimation of the model is in progress; we plan to analyze the welfare effect of alternative policies to encourage migration, such as access to credit and further reductions in the cost of migrating.

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1 Introduction

Income in developing countries, particularly for rural households, is characterized by a high degree of year-to-year volatility, as well as large seasonal (within-year) fluctuations. How can households insure themselves against income risk in the presence of highly covariate income processes?

We study the role of temporary seasonal migration, and how migrating interacts with risk-coping mechanisms. In particular, we study the interaction between migration and informal risk sharing. Informal risk sharing summarizes the complex systems of inter household transfers exist to help households smooth income shocks ex post.

Our empirical setting is Northern Bangladesh, a location where there is both a large degree of seasonality to income, as well as large year-to-year fluctuations in income. Previous work in this setting found large returns to randomly inducing households to send a migrant to work in the city during the lean, "hungry" period of the year where agricultural work in the village is sparse (Bryan et al., 2014). In particular, providing migrants with a small ($8.50) cash or credit incentive, approximately equal to the return bus fare between the village and the city, i) increased migration rates out of the village by 30 percentage points; ii) increased consumption of the family members left behind in the village by 30%, and iii) one year after the subsidies were removed, migration remained 15 percentage points higher. However, changing the options available to migrate may also affect other methods of smoothing income risk, such as informal insurance Morten (2013). In this paper, we quantity the amount of interaction between migration and informal insurance using the experimental design to randomly change the prevalence of seasonal migration.

To do so, we study a model where migration and risk sharing are jointly determined. Changing the costs of migration, for example through experimentally providing incentives to migrate, changes the equilibrium in the village. In the model, risk sharing is constrained by limited commitment: the outside option (the value of consuming the autarkic income stream) is the key determinant of risk sharing. In the model, changing the ease of migration experimentally directly affects the outside option of households. In our model, this can have two effects. On one hand, the ability to migrate increases the outside option of households and decreases risk sharing. On the other hand, migration allows the network to smooth the impact of aggregate shocks, which may increase risk sharing.

We proceed as follows. In Section 2 we review the empirical setting. In Section 3 we undertake a reduced form analysis, building on the tests developed in Townsend (1994). We then progressively put more structure on the data. In Section 4 we undertake a semi-parametric analysis, following the methodology of Blundell et al. (2008). Then, we outline the model and the planned structural estimation, which is in progress, in Section 5. Section 6 briefly concludes.

2 Data

The empirical setting of the data is Rangpur, in North-west Bangladesh. The population of this area is 9.6 million, of which 5.3 million are below the poverty line. This is an area prone to a seasonal famine, known as *monga*. During the *monga* period, which occurs during September-November, prior to the harvest of the Aman rice harvest, consumption levels drop dramatically. This is shown in Figure 1.

The experiment, fully described in Bryan et al. (2014), was carried out between 2008-2013. The experiment was spread over two districts, covering 100 villages. In each village, 19 households were randomly selected from from the set of households that reported (a) having low levels of landholding and (b) that a household member had to skip at least one meal during the prior monga season (56% of households satisfied both criteria).

The experiment itself was multi-pronged. There were three key treatments: a cash incentive (conditional on migrating), a credit incentive (conditional on migrating) and an information treatment. Households in 37 villages were randomly assigned to the cash treatment; 31 assigned to the credit treatment; 16 assigned to the information treatment and 16 were control. The cash and credit treatment were each 600 taka ($8.50), approximately the cost of a return bus ticket and a few days food in the destination. The baseline was collected in July 2008, prior to the 2008 *monga*. In July 2011 data collection the experiment was expanded to a further 33 villages. In total, five rounds of data were collected.

In most rounds, detailed data on income, consumption, and migration episodes was collected. Table 1 gives a summary timetable of the data collection and dates of each data round.

This experiment had three main effects.[1] First, migration rates increased by 22 percentage points in treatment villages in the year in which financial incentives were offered. Second, treated villages were 8-10 percentage points more likely to migrate 1 and 3 years after the migration incentives we removed. Third, migration had positive returns on average: the consumption of family members left behind increased by approximately 30%. Refer to Bryan et al. (2014) for a full description of the experimental effects. The distributions of total income and total consumption, all in per capita terms, are given in Figure 2. The treatment villages have an increase in both income and consumption compared to the control villages.

Table 2 gives the summary statistics for the sample we use for the estimation. We want to construct annual versions of incomes and consumption, for this reason we use data collected during rounds 1,4 and 5, and discard rounds 2 and 3; round 2 because the income measure was only asked for the previous 4 months, not previous year; round 3

[1]The cash and credit treatment had the same effect on outcomes; in what follows these are bundled as "treatment". The information treatment was not successful at inducing migration and these villages are combined with the control villages.

because income was not collected.[2]

3 Reduced form tests

To first investigate the effect of increasing migration on risk sharing we undertake an omnibus test of risk sharing, based on the specification in Townsend (1994). We test whether the effect of income on consumption has changed in the treatment villages. The specification is:

$$\log C_{ivt} = \delta_i + \gamma_{vt} + \xi_0 \log Y_{ivt} + \xi_1 (\log Y_{ivt} * T_v) + \xi_2 (\log Y_{ivt} * post) + \beta (\log Y_{ivt} * T_v * post) + \epsilon_{ivt}$$

where $\log C_{ivt}$ and $\log Y_{ivt}$ are houshold i's log per capita consumption and income, respectively, T_v is an indicator variable taking the value 1 if the village is a treatment village; *post* is an indicator for the time period occurring after the start of the experiment (i.e., round 2 on).[3] We control for village-year fixed effects to control for aggregate shocks.

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[2]As seen in Table 2 there is a gap between measured income and consumption. There are several possible explanations for this gap:

1. Seasonality: November is the leanest season, so we would expect consumption > income especially for Rd
2. Price indices used: The average price for rice in the production data is 11 Taka. In the consumption data, is 16 Taka. We adjust the price indices so that production is valued at the same prices as consumption. [cdm: this didn't change things much because many of the households don't report crop income!]
3. Participation in social security programs. A large fraction of our sample receive public assistance. This may take the form of food aid, hence increasing consumption [why wouldn't our measures pick this up? cdm: it would be measured as consumption, but it is not in our income measure, mostly because we decided social programs are like "ex-post" income and therefore if included as income it won't look like insurance.]
4. Microfinance: almost all of the survey respondents are part of a microfinance group. We know from previous work that microfinance often used for consumption.
5. Timing of survey questions: asked income expenditure over last year. Due to timing, possible that reporting most recent expenses for crop that hasn't harvested yet, and harvest from last year. This may lead to recall error in income.
6. Could just be missing a section of income: hard to collect well.

[3]Consumption and income are converted into per capita terms by dividing by the number of household members who have been present in the house for at least seven days.

The results are in Tables 3. Columns (1) - (3) have the dependent variable of log of per capita total consumption. Columns (4) - (6) repeat the analysis with the dependent variable the log of per capita food consumption. For both total consumption and food consumption, income and consumption are positively correlated: in the first two specifications, a 10% increase in income corresponds to a 0.8% increase in consumption. The interaction test, $\log Y_{ivt} * T_v * post$ is negative and statistically significant: treatment reduces the correlation between income and total consumption by 6-8%. This is consistent with the treatment improving risk-sharing in the villages: the correlation between income and consumption decreases in treatment villages.

Tables 4 repeat the analysis only for the sample of households who did not migrate.[4] This addresses concerns about whether specific changes in how income was collected between migrant and non-migrant households, for example, caused the previous result. For example, if it became more difficult to measure household income for households with migrant members this may mechanically downward bias the relationship between income and consumption. The results hold when just examining the effect of being in a treatment villages for households who do not migrate: treatment reduces the correlation by 6-10%. This is consistent with migration changing the endogenous equilibrium in the risk sharing network; it is not just those who chose to participate in migration who are affected.

4 Semi-parametric model of income and consumption

We next turn to a semi-structural analysis to decompose the sources of income risk, and how the experiment changed the pass through of income risk into consumption. We undertake a decomposition of risk, building on and extending the framework developed in Blundell et al. (2008). In particular, we consider both permanent and transitory income shocks, each of which can either be idiosyncratic or aggregate to the village, and test how the experiment affected insurance of these shocks. By isolating different types of shocks

[4] This specification does not include baseline data because migration data was not collected, so the modified specification is $\log C_{ivt} = \delta_i + \gamma_{vt} + \xi_0 \log Y_{ivt} + \xi_1 (\log Y_{ivt} * T_v) + \beta (\log Y_{ivt} * T_v) + \epsilon_{ivt}$

and the differential transmission of these shocks to consumption, we complement and improve upon the Townsend tests by (1) explicitly accounting for measurement error, which is a concern in income and consumption data, especially in developing countries, and (2) pinpointing which types of insurance were affected by the experiment.

To proceed, we first specify a semi-structural model of consumption and income.

4.1 Income

We model the log income of household i at time t as a permanent-transitory process (MaCurdy, 1983; Abowd and Card, 1989; Meghir and Pistaferri, 2004) which is a function of three main components: (1) a permanent component P_{it}, (2) a transitory component e_{it}, and (3) measurement error x_{it}.

$$\log Y_{it} = P_{it} + e_{it} + x_{it}$$

The transitory component is serially uncorrelated and the permanent component follows a random walk in which the innovation, u_{it}, is serially uncorrelated.

$$P_{it} = P_{i,t1} + u_{it}$$

Growth in log income is then a function of permanent and transitory income shocks, along with measurement error.

$$\Delta logY_{it} = u_{it} + e_{it} - e_{i,t-1} + x_{it} - x_{i,t-1}$$

We then decompose these income shocks into shocks that are (a) aggregate to the village or (b) idiosyncratic to the household. We define u_{vt} as the aggregate permanent shock to village v at time t and u_{ivt} as the idiosyncratic permanent shock to the household such that $u_{vt} + u_{ivt} = u_{it}$. Analogously, let $e_{vt} + e_{ivt} = e_{it}$ for transitory shocks. Then we can rewrite income growth as:

$$\Delta y_{ivt} = \Delta \log Y_{ivt} = \underbrace{u_{ivt} + u_{vt}}_{\text{Permanent components}} + \underbrace{(e_{ivt} - e_{i,v,t-1}) + (e_{v,t} - e_{v,t-1})}_{\text{Temporary components}} + \underbrace{x_{ivt} - x_{i,v,t-1}}_{\text{measurement error}}$$

By definition, the sum of the idiosyncratic shocks across households in a village is zero for both permanent and transitory shocks:

$$\sum_{i=1}^{N_v} u_{ivt} = 0$$

$$\sum_{i=1}^{N_v} e_{ivt} = 0$$

4.2 Consumption

We define the growth in log consumption with two main components: (1) the pass-through of income shocks and (2) the change in measurement error. The growth in consumption between period t and $t+1$ is given by:

$$\Delta c_{ivt} = \Delta \log C_{ivt} = \underbrace{\delta_i u_{ivt} + \delta_v u_{vt}}_{\text{Insurance permanent shocks}} + \underbrace{\gamma_i e_{ivt} + \gamma_v e_{vt}}_{\text{Insurance temporary shocks}} + \underbrace{y_{ivt} - y_{i,v,t-1}}_{\text{measurement error}}$$

where δ_v and δ_i measure the pass-through of aggregate and idiosyncratic permanent income shocks, respectively, and γ_v and γ_i measure the pass-through of aggregate and idiosyncratic transitory income shocks, respectively. Measurement error in consumption is denoted by y_{ivt}.

4.3 Identification

We use covariance restrictions on the income and consumption processes described in Sections 4.1 and 4.2 to identify the parameters of interest in our model. The resulting set of parameters are (1) the transmission parameters δ_v, δ_i, γ_v, and γ_i, (2) permanent income variances $\mathrm{var}(u^v)$ and $\mathrm{var}(u^i)$ and transitory income variances $\mathrm{var}(e^v)$ and $\mathrm{var}(e^\imath)$, and (4) measurement error variances for income $\mathrm{var}(x)$ and consumption $\mathrm{var}(y)$. We allow transmission parameters and measurement error variances to vary across treatment and control. To identify parameters, we use covariances that exploit both time and within-village dimensions. For the within-village dimension, we construct a village-average measure:

$$\Delta\bar{y}_{ivt} = \frac{1}{N_v}\sum_{i=1}^{N_v}\Delta\log Y_{ivt} = u_{vt} + (e_{vt} - e_{v,t-1}) + \frac{1}{N_v}\sum(x_{ivt} - x_{i,v,t-1})$$

$$\Delta\bar{c}_{ivt} = \delta_v u_{vt} + \gamma_v e_{vt} + \frac{1}{N_v}\sum(y_{ivt} - y_{i,v,t-1})$$

These measures, which do not involve idiosyncratic shocks, will be used to identify village-aggregate parameters from idiosyncratic parameters. We then combine the consumption and income restrictions implied by the model to get a system of moment restrictions, given below:

1. Income moments

$$\mathrm{cov}(\Delta y_{i,v,t}, \Delta y_{i,v,t}) = \mathrm{var}(u^i) + \mathrm{var}(u^v) + 2\mathrm{var}(e^i) + 2\mathrm{var}(e^v) + 2\mathrm{var}(x) \tag{1}$$

$$\mathrm{cov}(\Delta y_{i,v,t}, \Delta y_{i,v,t+1}) = -\mathrm{var}(e^i) - \mathrm{var}(e^v) - \mathrm{var}(x) \tag{2}$$

$$\mathrm{cov}(\Delta\bar{y}_{i,v,t}, \Delta\bar{y}_{i,v,t}) = \mathrm{var}(u^v) + 2\mathrm{var}(e^v) + \frac{2}{N_i}\mathrm{var}(x) \tag{3}$$

$$\mathrm{cov}(\Delta\bar{y}_{i,v,t}, \Delta\bar{y}_{i,v,t+1}) = -\mathrm{var}(e^v) - \frac{1}{N_i}\mathrm{var}(x) \tag{4}$$

2. Consumption moments

$$\mathrm{cov}(\Delta c_{i,v,t}, \Delta c_{i,v,t}) = \delta_i^2\mathrm{var}(u^i) + \delta_v^2\mathrm{var}(u^v) + \gamma_i^2\mathrm{var}(e^i) + \gamma_v^2\mathrm{var}(e^v) + 2\mathrm{var}(y) \tag{5}$$

$$\mathrm{cov}(\Delta c_{i,v,t}, \Delta c_{i,v,t+1}) = -\mathrm{var}(y) \tag{6}$$

$$\mathrm{cov}(\Delta\bar{c}_{i,v,t}, \Delta\bar{c}_{i,v,t}) = \delta_v^2\mathrm{var}(u^v) + \gamma_v^2\mathrm{var}(e^v) + \frac{2}{N_v}\mathrm{var}(y) \tag{7}$$

$$\mathrm{cov}(\Delta\bar{c}_{i,v,t}, \Delta\bar{c}_{i,v,t+1}) = -\frac{1}{N_v}\mathrm{var}(y) \tag{8}$$

3. Moments crossed with income:

$$\text{cov}(\Delta c_{i,v,t}, \Delta y_{i,v,t}) = \delta_i \text{var}(u^i) + \delta_v \text{var}(u^v) + \gamma_i \text{var}(e^i) + \gamma_v \text{var}(e^v) \tag{9}$$

$$\text{cov}(\Delta c_{i,v,t}, \Delta y_{i,v,t+1}) = -\gamma_v \text{var}(e^v) - \gamma_i \text{var}(e^i) \tag{10}$$

$$\text{cov}(\Delta \bar{c}_{i,v,t}, \Delta \bar{y}_{i,v,t}) = \delta_v \text{var}(u^v) + \gamma_v \text{var}(e^v) \tag{11}$$

$$\text{cov}(\Delta \bar{c}_{i,v,t}, \Delta \bar{y}_{i,v,t+1}) = -\gamma_v \text{var}(e^v) \tag{12}$$

Using these 12 moment conditions allows us to identify the 10 parameters determining income, consumption and measurement error. The steps for computing this are in Appendix A.1.[5] Notably, because transitory shocks and income measurement error do not enter identically when we incorporate village-average moments, we can separately identify the two variances. It is well known that measurement error in income may be large in developing country datasets, but this is one of the first analyses to identify and quantify the magnitude.

4.4 Results

The model is estimated by GMM with a diagonal weighting matrix (Altonji and Segal, 1996; Blundell et al., 2008).[6] We compute standard errors using block bootstrap, clustering at the village level (Hall and Jorowitz, 1996; Horowitz, 2001) to account for arbitrary serial correlation between households in a village.

We allow all parameters to vary by treatment status with the exception of income parameters. The ideal measure of income is a village counterfactual income in the absence of the experiment that we then relate to consumption; the treatment will affect the transmission of income shocks into consumption through (1) exacerbating limited commitment problem and (2) insuring against bad income shocks by allowing people to go get potentially better income in city. This measure does not vary by treatment status. We apply this logic in constraining the income parameters to be equal across treatment and

[5]The proof to identify parameters separately by treatment and control is in Appendix A.2.

[6]The moments used in estimation are modified to account for longer time-differences between rounds of data as well as differences in village size, which affect village-average moments. We omit the discussion of these details in this draft.

control villages. However, this assumption is not innocuous. In particular, if the treatment changes the selection of who migrates, then even if the underlying income process is the same between treatment and control villages, because we only *observe* income of those who choose not to migrate (and some remittance income), income of treatment and control households will appear to be different in the data. We will address this selection problem in the structural model by modeling the migration choice explicitly.

The goal of this variance decomposition exercise is to identify which part of insuring the income process changed. The empirical results are presented in Table 5. From the estimates below where income is constrained, there are many interesting features:

- Income measurement error is very similar to consumption measurement error and accounts for around 1/4 of the variance of income. Almost all true income variation comes from idiosyncratic shocks as opposed to village-aggregate shocks, and 2/3 of it comes from transitory shocks as opposed to permanent shocks.

- Permanent shocks are pretty well insured considering they are permanent, except village-aggregate permanent shocks that are not insured at all. It looks like treatment decreased insurance against permanent shocks.

- For control villages, transmission of transitory shocks are not well estimated so we can't tell difference between idio and agg transmission. Transmission of aggregate transitory shocks does not change with treatment, but idiosyncratic shocks are significantly better insured in treatment villages.

Consistent with the earlier reduced form results, we find that the main mechanism through which the experiment improved informal risk sharing is by improving the insurance of transitory idiosyncratic income shocks.

5 Joint model of risk sharing and migration

We now present a joint model of income and risk sharing. The model is based on Morten (2013). We follow the approach of Krueger and Perri (2010) and write the social planners optimization problem as the dual expenditure minimization problem.

In the model, migration is endogenous, with the decision to migrate being made after the realization of the income shock in the village. Migration itself is uncertain, with migration income only revealed after the migration decision has been made. Risk sharing is endogenous, and is constrained by limited commitment. Allowing migration will have two potentially offsetting effects on risk-sharing. On one hand, the outside option of households increases, potentially crowding out informal insurance by making participation constraints bind more tightly. On the other hand, migration allows households to insure against aggregate shocks, by increasing their out-migration from the village. This may improve risk-sharing.

We differentiate in the model between two points in time, within the same period: ex ante (of the migration decision) and ex-post (of the migration decision). Ex-ante of migration decision, the household receives an income draw in the village, and makes a decision about whether or not to migrate. Ex-post of the migration decision, the migration outcome is realized, and informal transfers, and consumption, occurs. We model migration as temporary so at the end of the period all migrants return to the village.

The state variables in the problem are i) the state of the world, which is denoted as y, and ii) the level of state-dependent expected (ex-ante) promised utility the agent has been promised by the social planner, $\tilde{w}_y$. Let J index the possible migration outcomes. Given the state variables, we then solve for:

1. The ex-post utility for each J outcome w_{ij}
2. The contemporaneous utility h_{ij}
3. The migration rule $\mathbb{I}$
4. Tomorrow's continuation values, $\tilde{w}_k$ for future village income state k (which depend on which j you get today and hence we will use the notation $\tilde{w}_{jk}$).

In the model risk sharing is constrained by limited commitment: because households cannot commit to making transfers in the future, all contemporaneous transfers must give the participant at least as much utility from continuing to participate in the risk sharing agreement as they would have if they exited the agreement and were in autarky.

This means that we need to track the value of autarky at the two sub-points within the time period: first, the value of autarky at the start of the period (ex-ante of the migration decision), where the participant only knows y and has an expectation over their migration outcome, and then the ex-post value of autarky, once the migration decision has been made and migration income uncertainty resolved.

Let the ex-ante value of autarky be given by the following functional equation. Ex-ante autarky only depends on the value of income in the village, y_i:[7]

$$\text{Ex ante autarky} \qquad \hat{\Omega}(y_i) = \max_{\mathbb{I}} \left\{ (1-\beta) \sum_j \pi_j \, u\left[(1-\mathbb{I})y_i + \mathbb{I}m_j, \mathbb{I}\right] \right\} + \beta \sum_k \pi_k \hat{\Omega}(y'_k)$$

And ex-post autarky, once both y_i (income in the village), m_j (income if migrated), and $\mathbb{I}$ (migration decision) have been resolved:

$$\text{Ex post autarky} \qquad \Omega(y_i, m_j, \mathbb{I}) = (1-\beta)\, u\left[(1-\mathbb{I})y_i + \mathbb{I}m_j, \mathbb{I}\right] + \beta \sum_k \pi_k \hat{\Omega}(y'_k)$$

We assume that migrating has a utility cost, $u(c, \mathbb{I}) = u(c) - d\mathbb{I}$. We will solve the social planners cost minimization problem. We can write $C(h_{ij}, \mathbb{I}) = u^{-1}(h + d\mathbb{I})$ as the cost to the social planner of providing h_{ij} level of contemporaneous utility.

[7] Alternatively, can write

$$\hat{\Omega}(y_i) = \sum_j \pi_j \Omega(y_i, m_j, \mathbb{I}^*)$$

where $\mathbb{I}^*$ is the migration that is optimal under autarky.

The social planner's cost minimization problem is then:

$$V(\tilde{w}, y) = \min_{\{w_j, h_j, \tilde{w}'_{jk}, \mathbb{I}\}} \sum_j \pi_j \left[\left(1 - \frac{1}{R}\right) C(h_j, \mathbb{I}) + \left(\frac{1}{R}\right) \sum_k \pi_k V(\tilde{w}'_{jk}, y'_k) \right]$$

$$\begin{aligned}
&\text{Ex-post participation constraint (this period)} && + \sum_j \mu_j \left[\Omega(y, m_j, \mathbb{I}) - w_j \right] \\
&\text{Ex-ante participation constraint (next period)} && + \sum_k \sum_j \gamma_{jk} \left[\hat{\Omega}(y'_k) - \tilde{w}'_{jk} \right] \\
&\text{Promise keeping constraint} && + \sum_j \alpha_j \left[w_j - (1-\beta) h_j - \beta \sum_k \pi_k \tilde{w}'_{jk} \right] \\
&\text{Budget constraint} && + \lambda \left[\tilde{w} - \sum_j \pi_j w_j \right] \\
&\text{Bounds for migration} && + \psi_1 \left(-\mathbb{I} \right) \\
&\text{Bounds for migration} && + \psi_2 \left(\mathbb{I} - 1 \right)
\end{aligned}$$

We plan to solve this problem by policy function iteration. The associated first order conditions, and the proposed algorithm, are in Appendix B.1. This is in progress.

6 Conclusion

Life in developing countries is risky. Households have several risk mitigation options to choose from. However, in order to understand the benefits of migration it is important to understand how migration interacts with other risk-mitigation strategies, such as informal insurance.

Using a large scale randomized experiment that incentived households to migrate we show the effects of increasing access to migration on informal risk sharing. We do this using three complementary analyses. First, we show that using an omnibus measure of risk sharing, the experiment improved risk sharing. We then decompose the sources of this effect, modifying the methodology from Blundell et al. (2008). We decompose the effect into the insurance pameters for four types of income risk: aggregate transitory shocks, idiosyncratic transitory shocks, aggregate permanent shocks and idiosyncratic permanent shocks. Using this decomposition, we find that the experiment improved insurance of the transitory idiosyncratic component of income. The last step of the analysis is to estimate a fully dynamic model of endogenous migration and insurance. Estimation of the model is in progress.

References

Abowd, John M and David Card, "On the Covariance Structure of Earnings and Hours Changes," *Econometrica*, 1989, *57* (2), 411–445.

Altonji, Joseph and Lewis Segal, "Small-Sample Bias in GMM Estimation of Covariance Structures," *Journal of Business & Economic Statistics*, 1996, *14* (3), 353–366.

Blundell, Richard, L Pistaferri, and I Preston, "Consumption inequality and partial insurance," *American Economic Review*, 2008.

Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak, "Under-investment in a Profitable Technology : The Case of Seasonal Migration in Bangladesh," *Econometrica*, 2014, (Forthcoming).

Hall, Peter and Joel Jorowitz, "Bootstrap Critical Values for Tests Based on Generalized-Method-of-Moments," *Econometrica*, 1996, *64* (4), 891–916.

Horowitz, Joel L., "The Bootstrap," in J J Heckman and E Leamer, eds., *Handbook of Econometrics*, Vol. 5 2001, pp. 3159–3228.

Khandker, Shahidur R., "Seasonality of income and poverty in Bangladesh," *Journal of Development Economics*, March 2012, *97* (2), 244–256.

Krueger, D and F Perri, "Public versus private risk sharing," *Journal of Economic Theory*, 2010.

MaCurdy, Thomas, "A simple scheme for estimatng an intertemporal model of labor supply and consumption in presence of taxes and uncertainty," *International Economic Review*, 1983, *24* (2), 265–289.

Meghir, Costas and Luigi Pistaferri, "Income variance dynamics and heterogeneity," *Econometrica*, 2004, *72* (1), 1–32.

Morten, Melanie, "Temporary Migration and Endogenous Risk Sharing in Village India," 2013.

Townsend, Robert M, "Risk and Insurance in Village India," *Econometrica*, 1994, *62* (3), 539–591.

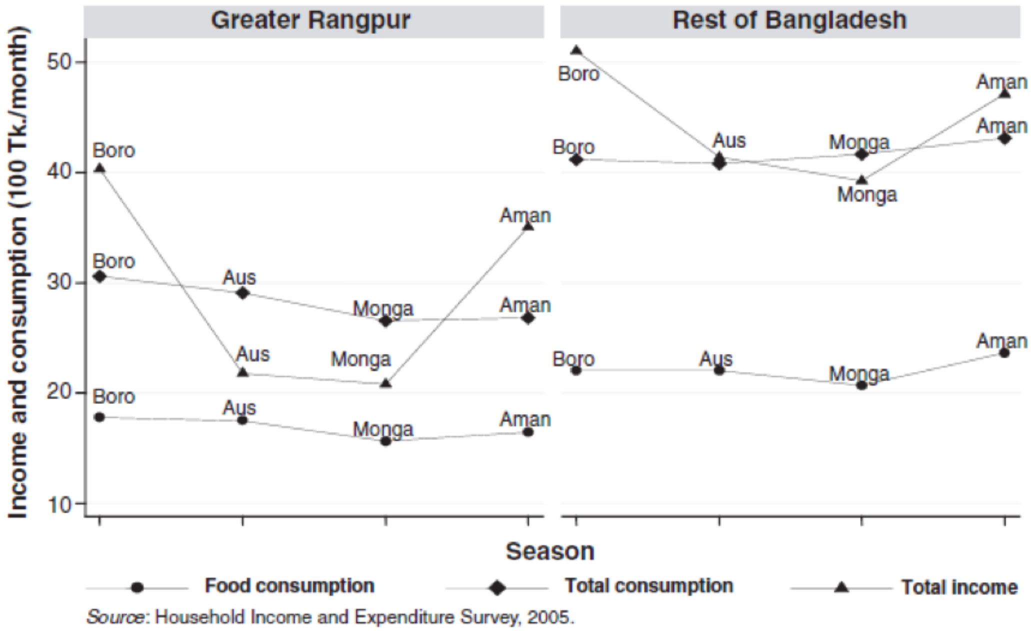
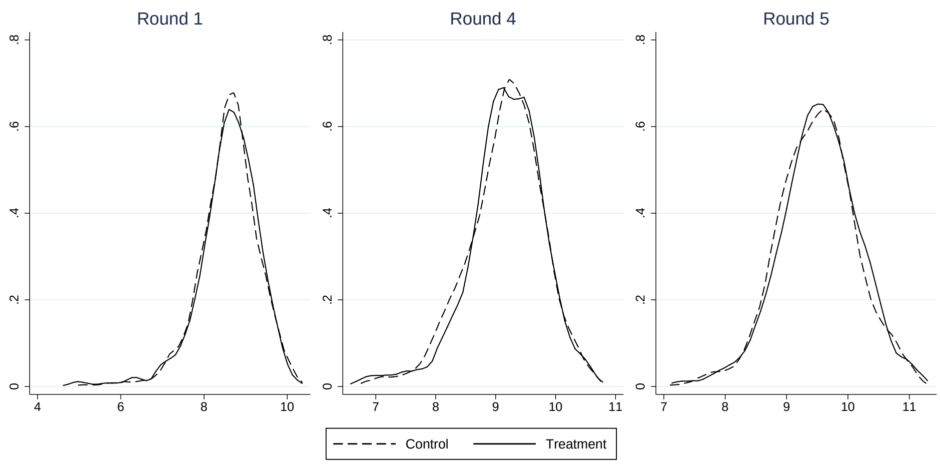


Figure 1: Consumption, by season: Rangur and rest of Bangladesh

Source: Figure 5 from Khandker (2012)

Panel A: Income



Panel B: Consumption

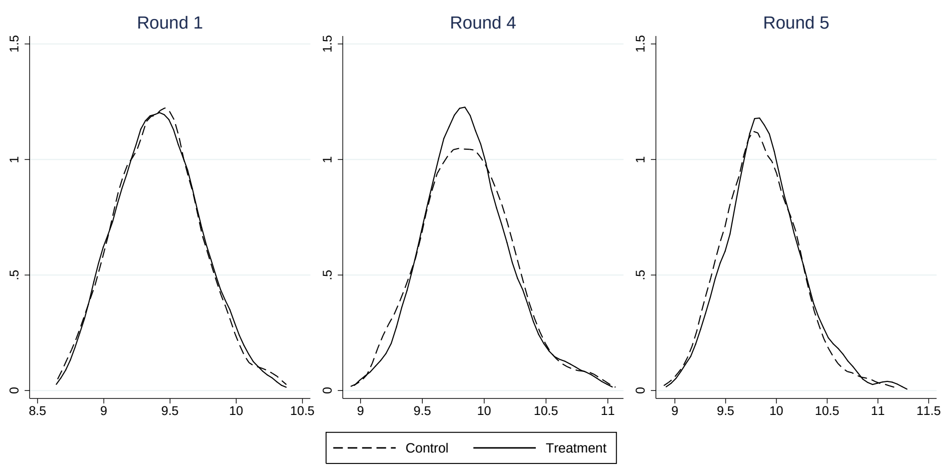


Figure 2: Kernel Densities for Income and Consumption

Kernel densities plotted for Round 1 (baseline; June 2008); Round 4 (2011) and Round 5 (2013). Income is log per capita monthly income; consumption is log per capita monthly total consumption.

Table 1: Experimental Design and Data Collection Timeline

Round	Date	Observations	Treat/control
1	July 2008 (planting)	1900 HHs, 100 villages	
2[a]	Nov 2008 (Monga)	1900 HHs, 100 villages	Cash, credit, info, control
3[b]	Nov 2009	1900 HHs, 100 villages	
4	July 2011	2527 HHs, 133 villages	Rain insurance, price insurance, credit, conditional credit, control
5	Dec 2013		Credit, job leads, control

[a] Income in rounds 1, 4, and 5 spans the previous 12 months. Income in round 2 spans the previous 4 months.

[b] Income data was not collected in round 3.

Table 2: Summary statistics

	Round 1			Round 4			Round 5		
mean/sd	Total	Control	Treatment	Total	Control	Treatment	Total	Control	Treatment
Total income	24.22	24.21	24.22	43.13	43.11	44.91	62.85	61.17	66.43
	(15.95)	(16.42)	(15.73)	(25.32)	(25.44)	(26.66)	(41.47)	(41.14)	(43.86)
Wage income	11.65	12.29	11.34	22.77	22.23	23.53	35.80	35.76	37.21
	(12.06)	(13.21)	(11.48)	(20.62)	(20.66)	(22.06)	(39.25)	(50.36)	(37.73)
Total consumption	46.67	46.58	46.72	77.95	79.91	80.87	79.48	76.74	83.21
	(17.12)	(17.39)	(17.00)	(33.80)	(33.68)	(34.84)	(36.91)	(34.37)	(38.85)
Food consumption	35.44	35.42	35.44	52.09	53.83	53.68	49.96	48.98	51.59
	(13.37)	(13.50)	(13.32)	(21.74)	(21.62)	(22.13)	(19.34)	(19.60)	(19.70)
Non-food consumption	11.01	10.83	11.10	25.09	25.29	26.23	28.85	27.52	30.44
	(5.83)	(5.89)	(5.81)	(16.39)	(15.62)	(16.99)	(23.52)	(21.53)	(24.03)
Daily per capita calories	2.07	2.06	2.07	2.32	2.32	2.37	2.25	2.22	2.28
	(0.51)	(0.50)	(0.51)	(0.64)	(0.62)	(0.65)	(0.66)	(0.65)	(0.67)
Household size	3.78	3.80	3.77	4.05	4.06	4.06	4.04	3.98	4.11
	(1.30)	(1.35)	(1.27)	(1.43)	(1.47)	(1.48)	(1.46)	(1.45)	(1.51)
Migrant household				0.41	0.36	0.44	0.39	0.30	0.40
				(0.49)	(0.48)	(0.50)	(0.49)	(0.46)	(0.49)
Number of households	1784	574	1210	1666	533	1133	1614	503	1111

Notes: Income and consumption are annual household levels in ’000s of Taka. Consumption and calories include only non-migrant consumption and calories. Income consists of wage, business, crop and other agriculture, asset income, other income such as lottery winnings or interest income, and (own) remittance income. Household size includes migrants. A migrant household is defined as a household that sent a migrant in the past four months. Round 1 did not collect this data.

Table 3: Townsend tests of risk-sharing

	(1) log PC cons	(2) log PC cons	(3) log PC cons	(4) log PC food	(5) log PC food	(6) log PC food
log PC inc	0.0872***	0.0823***	0.0421	0.0917***	0.0861***	0.0334
	(0.027)	(0.028)	(0.035)	(0.025)	(0.026)	(0.033)
treat*log PC inc	0.0427	0.0493	0.0426	0.0450*	0.0547*	0.0740*
	(0.029)	(0.030)	(0.041)	(0.027)	(0.029)	(0.039)
post*log PC inc	0.0894***	0.113***	0.0885**	0.0646**	0.0995***	0.0945***
	(0.030)	(0.033)	(0.035)	(0.028)	(0.031)	(0.035)
treat*post*log PC inc	-0.0593*	-0.0802**	-0.0630	-0.0747**	-0.0956***	-0.112***
	(0.034)	(0.037)	(0.042)	(0.032)	(0.035)	(0.041)
Village FE?	Yes	No	No	Yes	No	No
Village-round FE?	No	Yes	Yes	No	Yes	Yes
Household FE?	No	No	Yes	No	No	Yes
Observations	5067	5067	5067	5071	5071	5071
R-squared	0.379	0.421	0.715	0.289	0.340	0.669

Standard errors in parentheses clustered at village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns use annual per capita log income. Columns (1)-(3) use annual per capita log total consumption and columns (4)-(6) use annual per capita log food consumption.

Table 4: Townsend tests of risk-sharing, non-migrants

	(1) log PC cons	(2) log PC cons	(3) log PC cons	(4) log PC food	(5) log PC food	(6) log PC food
log PC inc	0.176***	0.205***	0.164**	0.159***	0.197***	0.141**
	(0.017)	(0.019)	(0.071)	(0.012)	(0.015)	(0.065)
treat*log PC inc	-0.0423*	-0.0627**	-0.105	-0.0478**	-0.0695***	-0.104
	(0.023)	(0.026)	(0.092)	(0.020)	(0.023)	(0.083)
Village FE?	Yes	No	No	Yes	No	No
Village-round FE?	No	Yes	Yes	No	Yes	Yes
Household FE?	No	No	Yes	No	No	Yes
Observations	1972	1972	1972	1981	1981	1981
R-squared	0.157	0.226	0.829	0.150	0.235	0.826

Standard errors in parentheses clustered at village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns use annual per capita log income. Columns (1)-(3) use annual per capita log total consumption and columns (4)-(6) use annual per capita log food consumption.

Table 5: Semi-structural model of income and consumption

	Control	Treatment	Difference
Income variances			
Perm idio	0.079	–	–
	(0.014)	–	–
Perm vagg	0.005	–	–
	(0.003)	–	–
Tran idio	0.147	–	–
	(0.058)	–	–
Tran vagg	0.012	–	–
	(0.004)	–	–
Measurement error variances			
Income	0.071	0.071	-0.000
	(0.053)	(0.060)	(0.036)
Consumption	0.062	0.072	0.010
	(0.003)	(0.003)	(0.004)
Transmission parameters			
Perm idio	0.107	0.249	0.141
	(0.096)	(0.051)	(0.100)
Perm vagg	0.934	1.039	0.105
	(0.265)	(0.296)	(0.283)
Perm agg - idio	0.827	0.790	–
	(0.280)	(0.313)	–
Tran idio	0.236	0.017	-0.219
	(0.104)	(0.036)	(0.116)
Tran vagg	0.133	0.140	0.007
	(0.297)	(0.364)	(0.413)
Tran agg - idio	-0.103	0.123	–
	(0.320)	(0.366)	–

Standard errors in parentheses based on 50 bootstrap replications, clustered at the village level. Moments are diagonally weighted.

A Semi-structural model of income and consumption

A.1 Identifying semi-structural model

- Adding twice(4) to (3) identifies $\text{var}(u^v)$ and adding twice (2) to (1) identifies $\text{var}(u^i)$.
- (6) identifies $\text{var}(y)$.
- Adding (11) to (12) identifies δ_v and subtracting (10) from (9) identifies δ_i.
- The combination of (7) and (12) identify $\text{var}(e^v)$ and γ_v and similarly, the combination of (10) and (5) identify $\text{var}(e^i)$ and γ_i.
- Finally, (1) identifies $\text{var}(x)$.

A.2 Identifying treatment effects

This section modifies the primary moment restrictions to show how we identify the parameters separately for treatment and control villages:

1. income moments

$$\text{cov}(\Delta y_{mivt}, \Delta y_{mivt}) = \text{var}(u^{mi}) + \text{var}(u^{mv}) + \text{var}(e^{mi}) + \text{var}(e^{ci}) + \text{var}(e^{mv}) + \text{var}(e^{cv}) + 2\text{var} \tag{13}$$

$$\text{cov}(\Delta y_{mivt}, \Delta y_{m,i,v,t+1}) = -\text{var}(e^{mi}) - \text{var}(e^{mv}) - \text{var}(x) \tag{14}$$

$$\text{cov}(\Delta \bar{y}_{mivt}, \Delta \bar{y}_{mivt}) = \text{var}(u^{mv}) + \text{var}(e^{mv}) + \text{var}(e^{cv}) + \frac{2}{N_v}\text{var}(x) \tag{15}$$

$$\text{cov}(\Delta \bar{y}_{mivt}, \Delta y_{m,\bar{i},v,t+1}) = -\text{var}(e^{mv}) - \frac{1}{N_v}\text{var}(x) \tag{16}$$

2. consumption moments

$$\text{cov}(\Delta c_{mivt}, \Delta c_{mivt}) = \delta_{mi}^2\text{var}(u^{mi}) + \delta_{mv}^2\text{var}(u^{mv}) + \gamma_{mi}^2\text{var}(e^{mi}) + \gamma_{mv}^2\text{var}(e^{mv}) + 2\text{var}(y) \tag{17}$$

$$\text{cov}(\Delta c_{mivt}, \Delta c_{m,i,v,t+1}) = -\text{var}(y) \tag{18}$$

$$\text{cov}(\Delta \bar{c}_{mivt}, \Delta \bar{c}_{mivt}) = \delta_{mv}^2\text{var}(u^{mv}) + \gamma_{mv}^2\text{var}(e^{mv}) + \frac{2}{N_v}\text{var}(y) \tag{19}$$

$$\text{cov}(\Delta \bar{c}_{mivt}, \Delta c_{m,\bar{i},v,t+1}) = -\frac{1}{N_v}\text{var}(y) \tag{20}$$

3. income x consumption moments

$$\text{cov}(\Delta c_{mivt}, \Delta y_{mivt}) = \delta_{mi}\text{var}(u^{mi}) + \delta_{mv}\text{var}(u^{mv}) + \gamma_{mi}\text{var}(e^{mi}) + \gamma_{mv}\text{var}(e^{mv}) \tag{21}$$

$$\text{cov}(\Delta c_{mit}, \Delta y_{m,i,t+1}) = -\gamma_{mi}\text{var}(e^{mi}) - \gamma_{mv}\text{var}(e^{mv}) \tag{22}$$

$$\text{cov}(\Delta \bar{c}_{mivt}, \Delta \bar{y}_{mivt}) = \delta_{mv}\text{var}(u^{mv}) + \gamma_{mv}\text{var}(e^{mv}) \tag{23}$$

$$\text{cov}(\Delta \bar{c}_{mivt}, \Delta y_{m,\bar{i},v,t+1}) = -\gamma_{mv}\text{var}(e^{mv}) \tag{24}$$

Identification of treatment-specific parameters (given that control parameters and measurement error variances are identified on the control villages):

1. (16) identifies $\text{var}(e^{mv})$ and then (24) identifies γ_{mv}.
2. (14) identifies $\text{var}(e^{mi})$ and then (22) identifies γ_{mi}.
3. (15) identifies $\text{var}(u^{mv})$ and then (23) identifies δ_{mv}.
4. (13) identifies $\text{var}(u^{mi})$ and then (21) identifies δ_{mi}.

B Structural model

B.1 First order conditions for cost minimization problem

The FOC of the cost-minimization problem yield:

$$\frac{\partial}{\partial w_j}: \quad \alpha_j - \mu_j = \lambda \pi_j \tag{1}$$

$$\frac{\partial}{\partial h_j}: \quad \left(1 - \frac{1}{R}\right) C_h(h_j, \mathbb{I}) = \alpha_j (1 - \beta) \tag{2}$$

$$\frac{\partial}{\partial \tilde{w}'_{jk}}: \quad \pi_j \pi_k \frac{1}{R} V_w(\tilde{w}'_{jk}, y_k) - \gamma_{jk} = \beta \alpha_j \pi_k \tag{3}$$

$$\frac{\partial}{\partial \mathbb{I}}: \quad \left(1 - \frac{1}{R}\right) \sum_j \pi_j C_{\mathbb{I}}(h_j, \mathbb{I}) + \sum_j \mu_j \Omega_{\mathbb{I}}(y_j, \mathbb{I}) = \psi_1 - \psi_2 \tag{4}$$

$$\textit{Envelope}: \quad V_w(\tilde{w}, y) = \lambda \tag{5}$$

$$\textit{Promise keeping}: \quad w_j = (1 - \beta) h_j + \beta \sum_k \pi_k \tilde{w}'_{jk} \tag{6}$$

$$\textit{Budget constraint}: \quad \tilde{w} = \sum_j \pi_j w_j \tag{7}$$

$$\textit{Comp slack 1}: \quad \mu_j \left[\Omega(y, m_j, \mathbb{I}) - w_j\right] = 0 \tag{8}$$

$$\textit{Comp slack 2}: \quad \gamma_{jk} \left[\hat{\Omega}(y'_k) - \tilde{w}'_{jk}\right] = 0 \tag{9}$$