Online Appendix "Returns to International Migration: Evidence from a Bangladesh-Malaysia Visa Lottery"

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Appendix A The G2G intermediation process

The following steps provide an outline of the G2G intermediation process.

- 1. Interested and eligible men apply for the G2G lottery program through their Union Information and Service Centers (UISCs). The application costs between BDT 50 and BDT 100.
- 2. Lottery winners are notified via text messages. Winners go to the BMET website to print their confirmation cards with detailed instructions.
- 3. Winners are asked to undergo a 10-day training at the closest Technical Training Centers (TTCs). Training is prepared following Malaysian government requirements.
- 4. Winners (mostly Phase-I) undergo a medical test in one of the nine medical colleges across Bangladesh.
- 5. TTCs prepare files for each applicant, which include copies of passport, full-size pictures, and biometrics, along with evidence of clearing the medical test and completing training and other required documents.
- 6. Individuals' files (scanned into DVDs) are sent to Malaysia. Malaysian firms decide which workers they want in their firms.
- 7. Malaysian government sends 'Visas With Referral' to the selected workers through BMET.1
- 8. BMET notifies the selected workers through SMS, asking them to come to the BMET office in Dhaka for final processing.
- 9. Workers submit their passports and necessary documents to BMET for visa processing. They also deposit recruitment fees at the Expatriates' Welfare Bank.
- 10. BMET conducts further processing to obtain visas as well as other documents, permits, and clearance.
- 11. Workers sign employment contracts. The contracts are typically for a two-year period with the possibility of renewal. Lodging is typically provided by the employers, whereas food may not always be provided. The contracts ensure a basic salary of MYR 900 and allow the possibility of overtime work.
- 12. BMET issues plane tickets for the workers.
- 13. BMET conducts pre-departure training the day before departure. Workers spend the night at the training camp and leave for Kuala-Lumpur the next day.
- 14. Migrant workers arrive in Kuala-Lumpur and are received by the employers in the presence of a representative from the Bangladesh High Mission in Kuala-Lumpur.

Appendix B Interpretation of the 2SLS estimates of returns to migration in light of alternative migration substitutes

The IV estimates derived from Equation (2) provide the causal estimate of the returns to migration for the *compliers* - those that were induced by winning the lottery to undertake migration. These compliers consist a mix of those who would have otherwise not migrated as well as those who would have undertaken migration independently to other destinations (especially, to the GCC countries). As Figure 3 shows, the program induced 70.1 percent of winner to migrate through the G2G channel. Of these, 12.2 percent (the difference in non-G2G migration between T1 and C) can be expected to have migrated on their own and the remaining 57.9 percent would not have migrated at all. In presence of substitutes, the 2-SLS estimate of the returns estimated in the paper is a weighted average of the returns to migration for those who would not have migrated otherwise and the returns to switching to G2G migration for those who would have migrated independently in absence of the program, where the weights are the share of compliers who would not have migrated otherwise (0.83 = 57.9/70.1) and share of compliers who would have switched (0.17 = 12.2/70.1) respectively.¹

To address this, we estimate a specification where we treat both G2G and non-G2G migration as endogenous (Table D.3). The lottery (T1) serves as the instrument for the G2G migration whereas the interaction of the lottery with the select covariates serve as instruments for the non-G2G migration.² We use pre-lottery measures of religion, household size, marital status, presence of a father as household head, and the Upazilas due to their predictive power in the control group. The returns to migration are similar when using only the lottery instrument (column 1) and when using the interaction instruments (column 2).

Column (3) of Table D.3 shows the result of the estimation where we instrument both types of migration. The interaction instruments could pose a problem for inference due to weak instrument concerns. However, a weak-instrument F-test (Sanderson & Windmeijer 2016) rejects this concern.

We fail to reject the equality of returns to G2G migration and non-G2G migration (p-value = 0.405). That is, the returns to (G2G) migration for those who switched from other independent migration is zero. In the presence of close substitute for the lottery losers who can migrate, the IV estimates serve as a lower bound to the returns to low-skilled temporary international migration. The returns to low-skilled international migration is 1.2 times (the reciprocal of 0.83, the share of compliers who would not have migrated otherwise) the IV estimates of the returns estimated in the paper.

¹See Kline & Walters (2016) for a formal derivation of the formula.

²Interacting experimental offer with covariates and location dummies is a common strategy to generate instruments in similar settings (e.g., Kline & Walters 2016, Kling et al. 2007, Abdulkadiroglu et al. 2014).

Appendix C Bounding exercise to address differential finding rates in the survey

C.1 Survey finding rates

With the field protocol described in Section 4, we were able to find and interview a higher share of T1 group compared to T2 and the control group. As Appendix Figure D.1 shows, the overall interview rates were 94 percent for T1, 69 percent for T2, and 68 percent for the control group. The large follow-up rate for T1 is seen in both the phone-based tracking as well as field-based tracking. While 47 percent of the control group were found through phone calls, conditional on having a phone, or getting phone numbers from fellow applicants, 55 percent of T1 were found and 89 percent of T2 were found. The reason for this discrepancy is that the phone records we got from BMET, albeit incomplete, were more up-to-date, as they kept interacting with the winners for further recruitment processes. Among respondents who we tracked on-field (all those not found by phone), the finding rate for the control group was about 40 percent whereas the finding rates for the treated groups were significantly higher at 89 percent and 64 percent for T1 and T2 respectively. Enumerators found it much easier to track the treated individuals in the villages because their information was more up to date with the local authorities. The winners had to interact with local authorities to submit the necessary information for their recruitment processing. Additionally, the treated applicants also became more well known in the local community as a result of winning the lottery.

C.2 Impact of differential finding rates

Common non-parametric bounding approaches, such as the Lee (2009) bounds are uninformative for many of our outcomes due to our particularly high finding rate in the treatment group (94 percent) relative to the control group (68 percent). This means that the Lee bounds approach drops the highest and lowest 27 percent of the outcome variables in the treatment group to construct the bounds. This extreme assumption naturally leads to wide and uninformative bounds. However, even under the extreme assumption of Lee bounds, migration and monthly income measure have bounds that are significantly different from zero (columns 2 and 3, Appendix Table D.6).

However, for other measures where the impact of the lottery is not very high, traditional Lee bounds estimate wide confidence intervals. This is partly because most of the outcomes are intermediated through migration. For instance, if migration leads to higher household expenditure, the Lee (lower) bound estimates of the ITT removes 27 percent of the migrants from the treated group with highest expenditures. That is, the share of migrants in the treated group falls from 76 percent to 49 percent, drastically reducing the power to detect reasonable impacts. Columns 2 and 3 of Appendix Table D.6 show this.

We next estimate the bounds assuming that we had not searched for any of the applicants in the field and completely relied on phone-based tracking. This is motivated by the high finding rate of 89 percent for group T1 compared to 40 percent for the control group (Appendix Figure D.1). However, even if we had just relied completely on phone-based tracking, there would still be a differential finding rate, as we would have found 55 percent of T1 and 44 percent of the control group. The Lee procedure will now remove 15 percent of the T1 sample to estimate the bounds, slightly better than in the full sample. Unfortunately, as columns 4 and 5 of Appendix Table D.6 show, the bounds are still too wide for outcomes other than income and migration measures.

Another approach we use to tighten the bounds derives from Behaghel et al. (2015) (henceforth

BCGL). This approach instruments the difficulty in finding respondents with some measure of effort exerted to find the respondents. The assumption of this approach is that, with enough effort, the finding rate would equate across treatment groups. This approach first selects different levels of effort in each treatment group in order to approximately balance the sample sizes and then runs a non-parametric procedure similar to the Lee procedure in the truncated data. BCGL apply this method in a setting where they use the number of phone call attempts made to locate the respondent as a truncating instrument. This approach often leads to much tighter bounds, as it incorporates additional information in constructing the bounds.

We follow the BCGL approach to construct bounds in our context as well. Columns 2 and 3 of Appendix Table D.7 show the BCGL bounds in our sub-sample of phone-found applicants. In this estimation, we treat as non-missing only the cases where respondents were found by phone (field found applicants are coded as missing). This procedure first truncates the treatment group that was found with more than two attempts (about 8 percent of the treatment group). The bounds are much tighter with this approach. Most of the key outcomes and indexes have bounds that are significantly different from zero.

However, the sample for whom we had phone numbers is a non-random subset of the treatment group. Among those we found, those for whom we had a phone number are more likely to be a migrant. In addition, the assumption that we only did phone-based tracking throws away 55 percent of the data. To incorporate the sample that was found in the field, we apply the BCGL intuition to construct another truncating instrument. Finding applicants is more difficult in highly populated unions. In our data, finding an increase in union population by 1 percent is associated with a fall in finding rate of 6 percentage points. Hence, we construct a truncating instrument which is defined as the number of phone call attempts for those for whom we had a phone numbers and the population decile of the union for those for whom we searched in the field. We qualitatively rank the phone attempts higher (low-effort) than population decile to reflect higher effort of finding someone in the field.

The BCGL bounds with this truncating instrument are presented in columns 4 and 5 of Appendix Table D.7. With this approach, the treated group is truncated at the top decile of population if they were not found through phone-based tracking. This results in tighter bounds for most of our estimates with bounds significantly different from zero for our key results. However, the BCGL bounds have some limitations in our context. Migration status, and treatment effect, differ by whether the respondent had a phone number. The BCGL, for example, constructs the bounds by comparing the control group with the treatment group that lives in lesser populated unions. This may introduce some bias or, at the least, change the interpretation of the impact.

Lastly, we resort to a pragmatic approach to characterize the likelihood of large bias due to differential finding rates. We assume that the higher finding rate of the treatment group is due to the artifact of winning the lottery and not some underlying characteristics that could directly affect the outcomes. With this assumption, we conduct 1 million monte-carlo simulations where we remove a random subset of the treatment group in order to match the finding rate and estimate the ITT on each of the samples. Column 6 of Appendix Table D.7 reports the proportion of the simulations in which we fail to reject the null of no effect. For most of our key outcomes, we do not fail to reject the null of no impact in a single simulation. We fail to reject null impacts on female decisionmaking index 17 times (0.0017%). Hence, any biases due to differential finding rates are extremely unlikely for our key outcomes. Only for one outcome (household with a loan), we fail to reject at a higher rate of 1.9%.

Finally, in Appendix Table D.8, we present the ITT and IV estimates on sub-samples restricted to unions where differential finding rates are low. We restrict to samples where the finding rates are

same for both treatment and control group (in columns 2 and 4) as well as to unions where the finding rates are within 25 percentage points of each other (in columns 3 and 6). The differential finding rates in these subsamples are, by construction, either the same (96 percent) or very similar (94 percent for treatment and 92 percent for control). As discussed earlier, unions where the finding rates were high are likely to have lower population. These smaller unions are likely to also have different characteristics (such as not being the main town or economic center). However, the table shows the ITT and IV estimates in these sub-samples are similar to the full sample. The differences are, in most cases, numerically small and statistically insignificant. The only meaningful differences are for the index of entrepreneurial activities where we see muted impact and for household consumption where we see increased impact in the sub-samples. These results are driven by lack of some entrepreneurial opportunities and lower levels of consumption among these households.

Appendix D Additional Figures and Tables

Appendix Figures

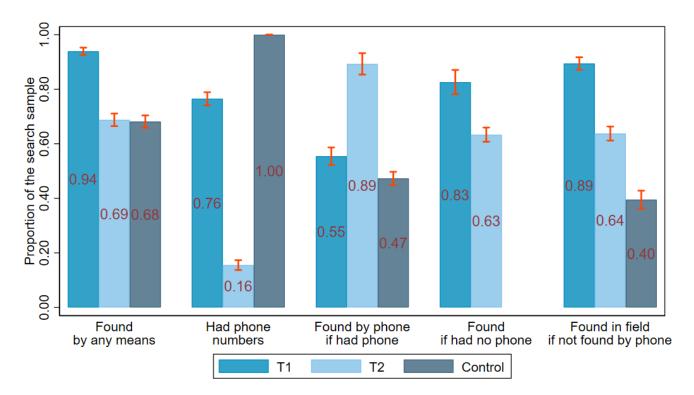


Figure D.1: Finding rates by treatment status and mode of search

Source: Authors' estimates from the survey data collected for this study.

Note: Figure shows the finding rates for the treated and control groups. The error bars show 95 percent confidence intervals.

Appendix Tables

		HIES 2016					
	Study sample	All	Rural	in survey divisions	with adult male		
	(1)	(2)	(3)	(4)	(5)		
A. Individual cha	racteristics	for men	aged 20-4	5			
Younger than 35 years	0.641	0.444	0.426	0.415	0.693		
		[0.000]	[0.000]	[0.000]	[0.001]		
Muslim	0.928	0.890	0.884	0.895	0.897		
T •	0.000	[0.000]	[0.000]	[0.000]	[0.001]		
Literate	0.808	0.689	0.657	0.675	0.685		
	6.000	[0.000]	[0.000]	[0.000]	[0.000]		
Completed years of education	6.833	5.592	4.994	5.097	5.152		
		[0.000]	[0.000]	[0.000]	[0.000]		
	ehold char						
Any migrant, last 5 years	0.249	0.087	0.101	0.149	0.074		
		[0.000]	[0.000]	[0.000]	[0.000]		
Any remittance income last year	0.250	0.029	0.033	0.050	0.020		
		[0.000]	[0.000]	[0.000]	[0.000]		
Per-capita consumption	$58,\!584$	55,204	48,722	54,578	50,811		
T (1 ,		[0.007]	[0.000]	[0.002]	[0.000]		
Log(per-capita consumption)	11.519	11.430	11.328	11.453	11.398		
\mathbf{D} (DDD ⁽¹⁾ 00 l)	0.007	[0.000]	[0.000]	[0.000]	[0.000]		
Poverty rate (PPP\$1.90 per day)	0.027	0.095	0.117	0.066	0.077		
Poverty rate (PPP\$3.20 per day)	0.267	[0.000] 0.430	[0.000] 0.503	[0.000] 0.394	[0.000] 0.434		
roverty rate (rrr\$5.20 per day)	0.207	[0.430]	[0.000]	[0.000]	0.454 [0.000]		
Per-capita income	54,944	57,120	[0.000] 47,411	50,851	[0.000] 49,639		
i ei-capita income	54,944	[0.346]	[0.000]	[0.073]	[0.015]		
Log(per-capita income)	10.967	11.151	11.023	11.087	11.097		
Log(per-capita income)	10.507	[0.012]	[0.441]	[0.108]	[0.085]		
Average age of HH members	26.05	29.10	29.56	28.71	25.09		
interage age of init memorie	20.00	[0.000]	[0.000]	[0.000]	[0.005]		
Average education among adults	5.90	4.50	3.95	4.10	4.48		
	0.00	[0.000]	[0.000]	[0.000]	[0.000]		
Household size	4.93	4.07	4.12	4.23	4.63		
		[0.000]	[0.000]	[0.000]	[0.000]		
Operates Non-farm business	0.436	0.179	0.164	0.156	0.191		
		[0.000]	[0.000]	[0.000]	[0.000]		
Farming Household	0.858	0.558	0.689	0.599	0.604		
		[0.000]	[0.000]	[0.000]	[0.000]		
Took loan in past year	0.734	0.302	0.332	0.280	0.317		
		[0.000]	[0.000]	[0.000]	[0.000]		

Table D.1: Comparison of study sample with the population

Source: Authors' calculations from the survey data collected for this study and HIES 2016.

Note: This table shows the comparison of the study sample with the Bangladeshi population along outcome measures indicated by the row headers. Panel A presents individual characteristics and Panel B presents household-level characteristics. The first column presents the mean for the control group in the study sample. The remaining columns presents the statistics for various subsamples of the nationally representative Household Income and Expenditure Survey of 2016/2017. Column 2 presents the national sample; column 3 restricts this sample to rural areas; column 4 further restricts the sample to rural household in the survey provinces of Dhaka, Mymensingh, and Chittagong; column 5 further restricts the sample to households with a male member between the ages of 20 and 45. For each subsample and outcome, the p-value from the test of equality of outcomes with the study sample is presented in brackets.

	(1)	(2)	(3)	(4)
	Control	Early treat-	Deferred	T1-T2
	mean	ment $(T1)$ -	expected	
		Control (C)	treatment	
		()	(T2)-C	
Age	34.01	-0.220	-0.383	0.164
		[0.460]	[0.212]	[0.608]
Height, inches	64.98	0.220	0.157	0.064
		[0.003]	[0.034]	[0.436]
Muslim	0.928	0.015	-0.025	0.040
		[0.124]	[0.024]	[0.000]
Can read and write	0.808	0.003	-0.007	0.010
		[0.854]	[0.666]	[0.511]
Completed years of education	6.83	-0.175	-0.020	-0.155
		[0.307]	[0.910]	[0.313]
Father is alive	0.588	-0.009	-0.004	-0.005
		[0.680]	[0.858]	[0.815]
Father's years of education	3.16	-0.255	0.157	-0.411
		[0.115]	[0.354]	[0.020]
Mother is alive	0.835	-0.009	0.004	-0.013
		[0.573]	[0.818]	[0.412]
Mother's years of education	1.67	-0.075	0.176	-0.251
		[0.505]	[0.167]	[0.051]
Married before lottery	0.615	-0.016	-0.024	0.008
		[0.383]	[0.247]	[0.710]
HH size before lottery	4.98	-0.185	-0.170	-0.015
		[0.107]	[0.147]	[0.889]
Months worked in 2012	11.37	-0.051	0.049	-0.100
		[0.497]	[0.487]	[0.145]
Average monthly income in 2012	8810	565.4	86.7	478.7
		[0.236]	[0.871]	[0.385]
Joint p-value across all outcomes		[0.225]	[0.339]	[0.319]

Table D.2: Balance of characteristics across treatment groups

Note: The table shows the relationship between individual characteristics and the treatment status. The first column shows the mean of the characteristic in the control group. The rest of the columns show the differences between various treatment groups as indicated in the column headers with p-values in brackets. Each row is estimated from a regression of the characteristic on the treatment indicators controlling for upazila fixed effects and standard errors clustered at the union level. The last row shows the p-value of a joint-test that all coefficients in each column are jointly zero.

	Basic	Multiple	Two endonegous
		instruments	variables
	(1)	(2)	(3)
Migrated abroad	1.133	1.109	
0	[0.000]	[0.000]	
G2G intermediated			1.179
			[0.000]
Non-G2G migration			1.609
			[0.009]
G2G = non-G2G (p-value)			0.405
		0 x 0 0	0.000
Overid. <i>p</i> -value		0.503	0.382
First-stage F -stat		35.217	[7.890; 3.559]
<i>p</i> -value		0.000	[0.000 ; 0.000]

Table D.3: 2-SLS estimates of returns to migration with interaction instruments

Source: Authors' calculations from the survey data collected for this study.

Note: This table shows the 2-SLS estimates of the impact of migration on the logarithm of monthly income (computed). Migration in column (1) is instrumented by the lottery status (T1). In column (2), T1 as well as its interaction with covariates (religion, household size, presence of a father as household head, and marital status at the time of the lottery and Upazila dummies) are used as instruments. In column (3), migration status is broken down into G2G and non-G2G migration and are instrumented by T1 as well as its interaction with covariates. Each column is a separate regression estimate with p-values in brackets. The table also presents p-values of overidentification tests, and the first stage F-stats (Sanderson & Windmeijer 2016) and p-values that test for weak instruments. Column (3) also presents the p-value of the test of equality of the two kinds of migration. All estimations control for applicant height, age, religion, parental education, and indicators for survey Upazilas. Standard errors are clustered at the union levels.

		Full sample	Only married applicants		
	(1) Married	(2) Educated spouse	(3) Spouse earnings	(4) Educated spouse	(5) Spouse earnings
Migrated	0719 [0.012]	0395 [0.338]	-1078 [0.007]	0277 [0.499]	-1027 [0.007]
x Unmarried in 2013		.0205 [0.776]	1424 [0.003]	.211 [0.043]	[1835] [0.007]
Unmarried in 2013		162 [0.000]	-1520 [0.000]	[.123] [0.012]	-1418 [0.000]
Control group mean	.804	.389	914	.484	1133

Table D.4: Impact of migration on marriage and spouse quality

Source: Authors' calculations from the survey data collected for this study.

Note: This table shows the IV estimates of the impact of migration on marriage and spouse quality. Migration and the interaction are instrumented by T1 and its interaction with the marital status at the time of the lottery. Outcomes are represented by the row headers. Educated spouse have at least eight years of schooling. Spouse earnings is measured in Bangladeshi Taka. Each column is a separate regression with p-values in brackets. In columns (2) and (3), spouse outcomes are set to zero for unmarried applicants. Columns (4) and (5) restrict the sample to married applicants. The estimations control for applicant height, age, religion, parental education, and indicators for survey Upazilas. Standard errors are clustered at the union levels.

Depvar:	(1)	(2)
Average monthly income (computed)	Took skills training	Invested in a
		Language
Migrated	1.150	1.312
	[0.000]	[0.000]
migrated x SKILL	0.316	-0.838
	[0.622]	[0.316]
SKILL	-0.285	0.561
	[0.545]	[0.435]
First-stage F-stats	[2.87; 2.99; 3.63]	[2.44; 1.89; 2.75]
p-value	[0.000; 0.000; 0.000]	[0.000; 0.000; 0.000]
Mean of SKILL among migrants	0.592	0.315
Mean of SKILL among non-migrants	0.148	0.039

Table D.5: Impact of skill acquisition on labor and income for migrants and non-migrants

Source: Authors' calculations from the survey data collected for this study.

Note: This table tests the impact of skill acquisition on labor and income for migrants and non-migrants. The measure of skill acquisition (SKILL) is indicated by the column heading. The dependent variable is the inverse hyperbolic sine transformation of the average monthly income (as defined in Table 1). The table presents the results of IV estimates on the full sample including T1, T2, and C groups. Lottery status (T1, T2) as well as their interaction with covariates (education, religion, household size, marital status, presence of father household head, and Upazilas) serve as instruments. Each column is a separate regression which controls for above mentioned covariates as well as applicant height, age, parental education, and indicators for survey Upazilas. Standard errors are clustered at the union levels. The p-values are shown in brackets. The Sanderson & Windmeijer (2016) test for weak instruments and the relevant p-values appear below the estimation results. The SKILL measure in column (1) indicates that the applicant took skills training; in column (2) it indicates that they took language training on Malay. The averages of the SKILL measures for migrants and non-migrants are also presented at the bottom.

	(1) Full sample	(2) (3) Lee bounds (full sample)		(4) Lee (phone	(5) bounds sample)
	ITT	Lower bound	Upper bound	Lower bound	Upper bound
Migrated abroad	0.571	0.483	0.806	0.611	0.783
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ihs(Total income, home and away)	0.570	0.225	0.998	0.468	0.965
	[0.000]	[0.022]	[0.000]	[0.000]	[0.000]
ihs(Remittance income)	4.555	2.303	7.725	3.290	6.368
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ihs(monthly income, computed)	0.721	0.288	1.381	0.466	1.302
	[0.000]	[0.004]	[0.000]	[0.002]	[0.000]
Index: Labor and Income	0.406	0.158	0.808	0.252	0.711
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
Log(Consumption per capita)	0.120	-0.149	0.359	-0.065	0.236
	[0.000]	[0.000]	[0.000]	[0.121]	[0.000]
Index: HH consumption	0.199	-0.247	0.657	-0.022	0.505
	[0.000]	[0.000]	[0.000]	[0.760]	[0.000]
Index: Investment in children	0.192	-0.153	0.594	-0.065	0.411
	[0.000]	[0.001]	[0.000]	[0.338]	[0.000]
Any loan	-0.052	-0.171	0.208	-0.110	0.062
	[0.007]	[0.000]	[0.000]	[0.001]	[0.145]
Index: Poverty and insecurity	-0.241	-0.685	0.132	-0.536	-0.056
	[0.000]	[0.000]	[0.005]	[0.000]	[0.448]
Index: Entrepreneurial	-0.198	-1.071	0.192	-0.527	0.004
	[0.000]	[0.000]	[0.000]	[0.000]	[0.957]
Index: Female decisionmaking	0.184	-0.414	0.639	-0.260	0.349
-	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Index: Pre-migration investments	2.599	1.401	4.145	1.943	3.054
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table D.6: Lee bounds on ITT est	stimates accounting for differential finding rates
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Note: This table shows non-parametric Lee bounds to address the differential finding rates on select outcomes indicated in the row headers. Column 1 shows the ITT estimate (unweighted) for reference estimated using Equation (1) on the sample including T1 and control group. Columns 2 and 3 shows the Lee (2009) bounds on the full sample. Columns 4 and 5 show the Lee bounds assuming that we had conducted surveys only among applicants who were found by phone. p-values of the estimates in brackets.

	(1) Full Sample	(2) BCGL (phone s	(3) bounds ample)	(4) BCGL (full sam	(5) bounds uple)	(6) Simulations
	ITT	Lower bound	Upper bound	Lower bound	Upper bound	Failure rate
Migrated abroad	0.571	0.633	0.664	0.571	0.586	0.000000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
ihs(Total income, home	0.570	0.622	0.723	0.555	0.596	0.000000
and away)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
ihs(Remittance income)	4.555	4.135	4.955	4.512	4.670	0.000000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
ihs(monthly income, computed)	0.721	0.668	0.825	0.708	0.754	0.000000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
Index: Labor and Income	0.406	0.337	0.433	0.387	0.418	0.000000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
Log(Consumption per capita)	0.120	0.079	0.158	0.100	0.121	0.000000
	[0.000]	[0.069]	[0.000]	[0.001]	[0.000]	
Index: HH consumption	0.199	0.106	0.272	0.179	0.228	0.000000
-	[0.000]	[0.180]	[0.000]	[0.003]	[0.000]	
Index: Investment in children	0.192	0.094	0.215	0.165	0.200	0.000000
	[0.000]	[0.195]	[0.000]	[0.000]	[0.000]	
Any loan	-0.052	-0.076	0.010	-0.056	-0.041	0.018765
U U	[0.007]	[0.056]	[0.736]	[0.012]	[0.228]	
Index: Poverty and insecurity	-0.241	-0.307	-0.152	-0.246	-0.197	0.000000
<i>. . .</i>	[0.000]	[0.000]	[0.046]	[0.000]	[0.001]	
Index: Entrepreneurial	-0.198	-0.265	-0.113	-0.205	-0.168	0.000000
	[0.000]	[0.000]	[0.250]	[0.000]	[0.001]	
Index: Female decisionmaking	0.184	0.028	0.226	0.163	0.210	0.000017
0	[0.000]	[0.730]	[0.028]	[0.011]	[0.001]	
Index: Pre-migration investments	2.599	2.405	2.792	2.562	2.676	0.000000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	

Table D.7: Behaghel et al. bounds on ITT estimates and simulations results

Note: This table shows non-parametric bounds to address the differential finding rate on select outcomes indicated in the row headers. Column 1 shows the ITT estimate (unweighted) for reference estimated using Equation (1) on the sample including T1 and control group. Columns 2 and 3 shows the Behaghel et al. (2015) (BCGL) bounds on the sample using phone call attempts as the truncating instrument. These bounds are estimated in that sample that were found through phone calls. Columns 4 and 5 shows the BCGL bounds on the full sample using a mix of phone call attempts and a measure of union population as the truncating instrument. The p-values for the estimates and bounds are presented in brackets. Column 6 shows the proportion of monte-carlo simulations in which we fail to reject the null of no effects of winning the lottery at 95 percent significance level. Each of the 1 million simulation chooses a random subset of the treatment group to match the finding rates between the treated and the control groups.

	(1)	(2)	(3)	(4)	(5)	(6)
		ITT estimate		IV estimate		
	All	Equal	within .25	All	Equal	within .25
Sample size	2239	963	1087			
Finding rate (treatment)	0.939	0.960	0.943			
Finding rate (control)	0.681	0.960	0.923			
Migrated abroad	0.580	0.556	0.548			
5	[0.000]	[0.000]	[0.000]			
ihs(Total income home and away)	0.612	0.721	0.667	1.085	1.338	1.249
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ihs(Remittance income)	4.362	3.827	3.646	7.520	6.886	6.649
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ihs(monthly income, computed)	0.657	0.610	0.577	1.133	1.095	1.051
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Index: Labor and Income	0.390	0.412	0.396	0.672	0.740	0.721
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Log(Consumption per capita)	0.116	0.143	0.136	0.200	0.258	0.248
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Index: HH consumption	0.216	0.259	0.247	0.372	0.467	0.450
-	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Index: Investment in children	0.191	0.192	0.163	0.329	0.346	0.296
	[0.000]	[0.001]	[0.003]	[0.000]	[0.000]	[0.002]
Any loan	-0.055	-0.054	-0.056	-0.095	-0.097	-0.102
•	[0.007]	[0.067]	[0.054]	[0.006]	[0.059]	[0.047]
Index: Poverty and insecurity	-0.256	-0.293	-0.269	-0.442	-0.527	-0.491
, , , , , , , , , , , , , , , , , , ,	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Index: Entrepreneurial	-0.190	-0.079	-0.092	-0.328	-0.143	-0.167
-	[0.000]	[0.180]	[0.109]	[0.000]	[0.162]	[0.094]
Index: Female decisionmaking	0.192	0.153	0.157	0.331	0.275	0.287
0	[0.000]	[0.030]	[0.020]	[0.000]	[0.021]	[0.013]
Index: Pre-migration investments	2.609	2.536	2.516	4.498	4.563	4.588
~	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table D.8: ITT and IV estimates on trimmed samples to match finding rates

Note: This table shows the ITT (columns 1-3) and IV (columns 4-6) estimates on various subsamples of the data. Columns 1 and 4 present the estimates in the full sample of T1 and control group. Columns 2 and 5 restrict the estimation to unions where the finding rates are identical. Columns 3 and 6 restrict the estimations to unions where the differential finding rate is below 25 percentage points. The first three rows shows the sample size and finding rates across these sub-samples. p-values for the estimates are shown in brackets.

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