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Returns to Low-Skilled International Migration

Evidence from the Bangladesh-Malaysia Migration Lottery Program

Mushfiq Mobarak
Iffath Sharif
Maheshwor Shrestha

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Abstract

Many economists believe that the returns to migration are high. However, credible experimental estimates of the benefits of migration are rare, particularly for low-skilled international migrants and their families. This paper studies a natural experiment in Bangladesh, where low-skilled male migrant workers to Malaysia were selected via a large-scale lottery program. This study tracked the households of lottery applicants and surveyed 3,512 lottery winners and losers. Five years after the lottery, 76 percent of the winners had migrated internationally compared with only 19 percent of the lottery losers. Using the lottery outcome as an instrument, the paper finds that the government intermediated migration increased the incomes of migrants by over 200 percent and their household per capita consumption by 22 percent. Furthermore, low-skilled international migration leads to large improvements in a wide array of household socioeconomic outcomes, including female involvement in key household decisions. Such large gains arise, at least in part, due to lower costs of government intermediation.

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Returns to Low-Skilled International Migration: Evidence from the Bangladesh-Malaysia Migration Lottery Program[*]

Mushfiq Mobarak[†] Iffath Sharif[‡] Maheshwor Shrestha[§]

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[†] Yale University, Deakin University, NBER and CEPR. Contact: ahmed.mobarak@yale.edu
[‡] The World Bank. Contact: isharif@worldbank.org
[§] The World Bank. Contact: mshrestha1@worldbank.org

1. Introduction

More than 270 million people, or 3.5 percent of the world's population, currently live outside their country of birth (UNDESA 2019). This reflects over 50 percent increase in the number of international migrants since 2000. While rich countries in North America, Europe, and Australia continue to host large numbers of migrants, destinations in Asia, such as Saudi Arabia, the United Arab Emirates, Malaysia, and Thailand, are also increasingly becoming popular destinations for migrants. Additional destinations in the Middle East, such as Qatar, Kuwait, and Oman, host a disproportionately large share of migrants relative to the native population. These new destinations have attracted a large number of temporary work migrants in recent years.

International migrants remitted $624 billion back to their home countries in 2018 (World Bank 2020). That makes remittances the most important international financial flow into developing countries, triple the size of Official Development Assistance, and easily surpassing any reasonable estimate of the gains to removing all trade barriers. Migration contributed an estimated 9.4 percent of global GDP in 2015 (McKinsey 2016). Remittances are a large share of the economy of several Asian countries, reaching 33 percent in Kyrgyz Republic, 29 percent in Tajikistan, and 28 percent in Nepal in 2018 (World Bank, 2020). Remittance incomes are also very important for large South Asian countries such as Pakistan (6.7 percent), Bangladesh (5.7 percent), and India (2.9 percent).

Despite the obvious importance of migration and remittances to the macroeconomy, there is a dearth of experimental evidence on the effects of migration opportunities on source countries and on families that migrants leave behind. This is particularly the case with the impacts of temporary work migration (for low-skilled work), which is becoming increasingly common. We attempt to fill this gap by taking advantage of a unique natural experiment in which the Government of Bangladesh allocated access to migration opportunities in Malaysia via a lottery program. More than 1.43 million men from rural areas across Bangladesh applied for the lottery which initially planned to send 30,000 workers for low-skilled agricultural work in palm-oil plantations in Malaysia under temporary two-year (renewable) contracts. The migrants were expected to leave their families behind and were not allowed to take up residency in Malaysia.

For this paper, we tracked down a sub-sample of the lottery applicants (or their families), both winners and losers, five years after the lottery. Our sample comprises of 3,512 applicants selected from three of eight administrative divisions of Bangladesh. By the time of the survey, 76 percent of the lottery winners had migrated internationally, compared to 19 percent of the lottery losers who form our control group. We find that low-skilled international migration, instrumented by the outcome of a randomized lottery, increases migrant income by over 200 percent and doubles their household income, mostly through increases in remittances sent from abroad. This further leads to improvement in welfare of the household along several measures of consumption, expenditures, and household debt position. Male migration drastically increases female involvement in key household decisions by over 0.5 standard-deviation, although this effect is likely to be, at least for now, driven mechanically by the absence of a key male member. We do not observe any differences in labor supply of other household members or changes in educational attainment of children (except an increase in educational expenditures). Household involvement in entrepreneurial activities falls, potentially due to the absence of the most entrepreneurial member of the household.

Our estimates provide a well-identified, microdata-based foundation to the results found from analysis of macroeconomic data (e.g. Clemens 2011, Clemens et al. 2018, Benhabib and Jovanovic 2012). Like the experimental estimates we report here, the macro literature reports income gains that are multiples of incomes at home, even for internal migration from rural to urban areas (Gollin et al. 2014).

We present evidence on the returns to migration in an especially consequential context. International migration is a very popular livelihood strategy in South Asia, and 10 percent of the Bangladeshi male labor force works abroad. South Asians moving temporarily to richer nations in Asia is one of the most popular global migration corridors. Each year, 2.2 million workers from four South Asian countries – Bangladesh, India, Nepal, and Pakistan – seek work-permit clearances to work abroad.[1] Of the 270 million migrants in the world, over 31 million are South Asians living in Asia outside their country of birth (UNDESA 2019). Bangladesh alone supplies almost 7 million migrants to other Asian countries. Malaysia now hosts 2.8 million Asian migrants. Our results are therefore representative of possibly the single most important migration corridor in the world. If we are to make confident inferences about the global economic effects of migration, we must investigate how South Asians fare when traveling to richer Asian nations.

The Bangladesh-Malaysia program we study is representative in another important aspect. The work visas are temporary, and do not offer a path to citizenship. This is typical of the temporary labor contracts that make up the lion's share of cross-border movements around the world. This is relevant

[1] Note that this is an underestimate of total migrant outflow from these countries, as many workers may migrate internationally without seeking a work-permit clearance from authorities.

for the broad external validity of our estimates, because migrants will obviously share and remit differently when they expect to return to the country of origin (Ashraf et al. 2014). The literature has produced estimates of the effects of permanent or high-skilled migration, but such movements are a small trickle compared to programs that take unskilled or semi-skilled South Asians to work temporarily in richer Asian nations. More than 15 million South Asian migrants work under such conditions on the Arabian Peninsula. Richer countries in East Asia like Malaysia, the Republic of Korea, Japan and Singapore have recently become increasingly popular as destinations, as they have also opened their doors to temporary labor migration to fill employment gaps. Migrants comprise large shares of the population in countries such as the United Arab Emirates (88 percent), Qatar (79 percent), Saudi Arabia (38 percent), and Singapore (37 percent). Through the sheer volume of migration opportunities, these countries contribute to South Asian development in a much more significant way than countries in Europe or North America. For example, about three-quarters of all remittances flowing into Bangladesh come from other Asian countries.

The specific migration facilitation program we study is novel in one respect: this was based on a direct Government-to-Government (G2G) agreement, bypassing the private sector intermediaries that migrants and employers are often forced to rely on. G2G mechanisms, particularly direct government involvement in providing intermediation services, have the potential to address several market failures that undermine the efficacy of private sector led intermediation. Due to the large demand for scarce jobs abroad, migration costs under the private sector are very high and can undermine the gains from migration (KNOMAD 2016). In addition, due to the inherent asymmetric information in the recruitment market, potential migrants further expose themselves to the risk of exploitation by unscrupulous agencies (UNODC 2015). The combination of high costs, the resulting indebtedness, and the risk of exploitation has led to severe policy concerns in both the sending and receiving countries. Policy backlash to these concerns, which often takes the form of a ban on migration flows, is often counterproductive. The Bangladesh-Malaysia G2G program was created to resolve such a ban. This program, though short-lived for various political reasons, was able to reduce migration costs by a factor of 8, contributing to the gains from migration that we observe in our data. Given the potential for G2G mechanisms to improve migration outcomes in a world where the inefficient spatial distribution of labor imposes a trillion-dollar cost on the global economy (Clemens 2011), this first rigorous evaluation of a G2G program has important implications for future policy design in many countries.

The large welfare gains we estimate in our data stand in sharp contrast to Gibson et al.'s (2010) estimates of the adverse effects of winning a New Zealand migration lottery program on the extended family members of Tongan emigrants who remained behind. That study is the closest to ours in terms of research design and rigor, but their setting is very different from ours in several important aspects. Most importantly, their lottery program was for permanent migration where the winner could migrate with their spouse and children to New Zealand. Hence, any effects measured in Tonga are for distant household members, who naturally would not share in as much of the gains from migration. In contrast, Bangladeshi migrants leave their families behind and remit a large share of their income back to their families in Bangladesh, which results in large gains for their families. Likewise, permanent migration programs like that between Tonga and New Zealand represent a relatively small share of the global flow of migrants.[2] The migration episodes we study in Bangladesh typify the most common form of global flows, with Bangladesh being one of the largest suppliers of such migrants.

Another closely related study, Clemens and Tiongson (2017), estimates the impacts of a G2G program for temporary migration from the Philippines to South Korea. They employ a regression discontinuity (RD) design around the potential migrants' performance on a mandated Korean language test and find large consumption increases with migration. Unlike this paper, however, they do not measure household income increases that can rationalize the large cross-country gap in wages observed in macroeconomic data (Clemens et al. 2018). Our paper also differs in the sample and representativeness. Applying to the Korean employment scheme required a high school degree, work experience, and Korean language ability. In contrast, applicants to the Bangladesh-Malaysia lottery program were lower skilled and more representative of the high volume of international migrants from developing countries. Their RD generates internally valid estimates for the set of applicants who invested in learning Korean but performed marginally on the language test. Marginal performance may be correlated with cognitive ability or other unobserved dimension of skill. In contrast, the impact of migration that we estimate generalizes more broadly to a large and policy relevant migrant population that is willing and able to migrate internationally for low-skilled work.

Our research is related to the very large literature that estimates the returns to migration but has had to grapple with difficult selection issues (Akee 2010, Grogger and Hanson 2011, Gibson et al 2013). Review papers by McKenzie and Yang (2010) and McKenzie (2012) cite studies that exploit exogenous variation in immigration policies to study the effects of international migration (Clemens 2010,

[2] For instance, the migration program only takes 250 Tongan migrants each year.

Dinkelman and Mariotti 2016, Kusunose and Rignall 2018). Others make use of a variety of non-experimental methodologies, including controls for observables (Adams (1998)), selection correction methods (Barham and Boucher (1998)), matching (McKenzie et al 2010), instrumental variables (Brown and Leeves (2007), McKenzie and Rapoport (2007), Yang (2008), Macours and Vakis (2010)), panel data techniques (Beegle, De Weerdt, and Dercon (2011)), and natural policy experiments such as discontinuities in eligibility for migration (Clemens and Tiongson, 2017) and migration lotteries (Clemens 2013, Gibson, McKenzie, and Stillman 2011, Mergo 2016). Our study is among the very few that overcomes the selection problem by exploiting a randomized lottery program. Even among these few, our paper is the only one that estimates the impact of migration in the context of low-skilled temporary migration; others focus on permanent migration to a developed country often among high-skilled workers.

Some studies use designed or natural policy experiments to study specific aspects of the migration experience, such as remittance cost (Aycinena et al. 2010), or employer monopsony power (Naidu et al. 2014). There is also a large literature on the broader socio-demographic effects of migration on children, health and family (Alcarez et al. (2012), Edwards and Ureta 2003; Yang 2008, Giannelli and Mangiavacchi 2010), which is well summarized by Antman (2012). Our results contribute to this literature as well.

The remainder of the paper is structured as follows: Section 2 describes the context of international migration in Bangladesh and the G2G migration lottery program; Section 3 describes the data collection and sampling strategy employed in this paper and outlines the empirical strategy; Section 4 discusses the impact of the lottery and migration on a host of outcomes; and Section 5 concludes.

2. Context

Bangladesh has a large outflow of workers temporarily migrating abroad for low-skilled work. Data from the Bureau of Manpower, Employment, and Training (BMET) show that the annual outflow of low-skilled workers from Bangladesh has increased from about 0.2 million workers in 2000 to well over 0.5 million in recent years (**Figure 1**). The outflow increased to a record high of 1 million workers in 2017, with over half of them going to Saudi Arabia. Historically, Saudi Arabia (30 percent), the United Arab Emirates (19 percent), Oman (12 percent), Malaysia (9 percent), Qatar (6 percent), and Singapore (6 percent) have been the major destination countries for low-skilled Bangladeshi workers.

Estimates suggest that about 10 percent of the Bangladeshi male workforce are international migrant workers.

Consequently, the remittances sent by these workers have become an important source of national income. Between 2000 and 2017, remittance inflows increased by almost seven times with an annual growth of about 12 percent. At its peak, between 2008 and 2012, remittances made up one-tenth of the national GDP, making them a significant source of national income. In 2015, Bangladesh was the 10th largest remittance-receiving country globally. Remittances from workers abroad have been one of the key drivers of poverty reduction in Bangladesh, and they continue to be a large share of household income for poorer households (Hill and Endara, 2019; World Bank, 2013, 2015).

Despite the importance to the economy, the process of migration is far from straightforward. Low-skilled migrants depend on a layer of agents for intermediation. Over 900 recruitment agencies in Bangladesh provide intermediation services for low-skilled jobs abroad (Das et al. 2018). Recruitment agencies in Bangladesh employ extensive layers of middlemen (*dalals*) to identify aspiring migrants, provide documentation services, and then place workers in jobs abroad.[3] This is a complex undertaking: a worker seeking to migrate must procure a national identity certificate, their birth certificate, a passport, bank account, contract, visa, a smart card containing identity documents, and a medical checkup; this list is not exhaustive (ILO, 2015).

The services of these middlemen are therefore essential to aspiring migrants, but the recruitment practices have raised some concerns. Anecdotes of fraudulent middlemen cheating migrants abound (Das et al. 2018). Recruitment agents often falsify documents and do not provide proper information about jobs abroad, which leads to many migrants finding the work abroad to be very different from what they had expected. In addition, migration costs in Bangladesh, often exceeding $4,500 (3.2 times GDP per-capita), are notoriously high compared to other sending countries (World Bank 2013; Farole and Cho, 2017). Most migrants borrow, often at high interest rates, to finance the high costs of migration. High indebtedness combined with fraudulent recruitment practices make migrants vulnerable to long-term indebtedness and further exploitation.

Such malpractices and concerns often translate to drastic and sub-optimal policy response from destination countries. As **Figure 1** shows, a steady outflow of migrant workers to Saudi Arabia

[3] The layered intermediation process and the associated services are a common feature of low-skilled migration form other South Asian countries as well (see for example Shrestha 2019, 2020).

stopped for seven years from 2008 to 2015 due to a ban imposed by Saudi Arabia in response to allegations of anomalies in the recruitment process.[4] Such bans are not rare. The ban imposed by the United Arab Emirates since 2013 is still in effect. Malaysia banned workers from 2008 to 2012, and again from 2019. In fact, the first ban provides the context of the lottery program.

The G2G migration lottery program

A state-managed recruitment system emerged as a solution to address concerns of malpractice in worker recruitment in the Bangladesh-Malaysia migration corridor. In November 2012, Bangladesh signed a memorandum of understanding (MOU) with Malaysia to recruit workers, in a limited scale, through a government-to-government (G2G) mechanism. This effectively ended the four-year ban on migration flows from Bangladesh to Malaysia. This mechanism meant that the government, and not private recruitment firms, would manage the recruitment process. The initial agreement was expected to send about 30,000 male workers from Bangladesh to work in the palm-oil sector of Malaysia. In early 2013, the Bangladesh Bureau of Manpower, Employment, and Training (BMET), under the Ministry of Expatriates' Welfare and Overseas Employment (MEWOE), started the recruitment process.

The recruitment process showed an overwhelming demand for migration opportunities. In January 2013, BMET started registering interested workers through all of its 4,529 rural Union Information and Service Centers (UISCs), the lowest-level administrative division in Bangladesh. To be eligible to apply, the applicant had to be male, aged between 18 and 45, at least 5 feet tall, at least 50kg or more in weight, and able to lift a weight of 20kg or more.[5] There was a small application fee of BDT 50-100 to register the application. During the two-week registration process, BMET registered 1.43 million applicants from all over rural Bangladesh. The overwhelming response suggests the high demand for opportunities to migrate abroad, even when these opportunities are known to be temporary (2-3 years), without the possibility of migrating with family members, and for work in low-skill manual jobs.

BMET conducted a first-lottery to select 36,038 workers to migrate under the G2G agreement. BMET wanted a fair process to select the workers from the pool of applicants and wanted to provide

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[4] https://www.reuters.com/article/bangladesh-saudi/saudi-arabia-lifts-ban-on-bangladeshi-workers-after-seven-years-ministry-idUSL3N1AS3NP

[5] Other eligibility criteria required that they have basic knowledge of Malaysian culture and social life; possess the ability to communicate either in English or Malay; have no prior criminal record; hold valid travel documents; and meet Malaysian medical fitness requirements.

opportunity to workers from all over Bangladesh. Hence, in February 2013, it conducted a randomized lottery with the probability of selection being proportional to the size of the population in the respective *upazila* (subdistrict). However, by this time, Malaysia had reduced its initial demand and wanted to recruit 30,000 workers over three phases.

BMET conducted a second lottery to divide the 36,038 workers into three phases, with the first-phase winners receiving immediate recruitment. To accommodate the request from Malaysia, BMET conducted a second lottery, again with probability proportional to the size of the upazila, to divide the initial winners into three phases. The lottery was designed to ensure that every union had at least one and at most five Phase 1 winners. The lottery produced 11,758 Phase 1 winners, 11,704 Phase 2 winners, and 12,576 Phase 3 winners. All winners were notified via SMS, and Phase 1 winners were asked to undergo a further recruitment process, which included a 10-day training and a basic medical screening exam. BMET started sending individual data and information on potential workers to Malaysia in March 2013, and by April 2013 it had already sent information on about 8,500 Phase 1 winners. Workers selected by Malaysia would then have the migration process initiated. [6]

The G2G initiative lost momentum shortly after its start and could not provide intermediation for Phase 2 and Phase 3 winners as they had expected. By June 2015, 2.5 years after implementation, only 7,616 lottery winners, most from Phase 1, were sent to Malaysia for work (Wickramsekara, 2016). The number had reached 9,892 as of March 2018.[7] This number is small relative to the original number agreed to with Malaysia, and it is also small relative to the volume of Bangladeshi workers willing to migrate abroad. The mechanism did not expand to other countries, or even to other sectors within Malaysia. The lack of involvement of the private sector recruiters is often argued as one the key reasons the G2G program failed to pick up steam. Newspaper articles and anecdotes also point toward issues both in Malaysia and Bangladesh and the nature of the recruiting environment, and not necessarily the program itself, as the reasons behind the program's losing steam (see, for example, Palma, 2015).

Migration to Malaysia has undergone several changes of mechanism in recent years. After the failure of the formal G2G mechanism, a G2G-plus mechanism was put in place, by which the private sector did the recruitment with the government providing regulatory oversight. This mechanism was able to intermediate more than 160,000 workers in a matter of a couple of years. However, this mechanism

[6] Please see Shah (2015) and Wickramasekara (2016) for more details on the program. A short description of the nature of intermediation is provided in the Appendix.
[7] Based on interviews with BMET officials managing the process.

also faced much criticism, as fewer than 10 recruitment firms in Bangladesh handled all the recruitment interactions with Malaysia. The concerns of high cost and malpractice reemerged, and the program has been suspended since mid-2018. Bilateral talks are currently underway to resolve the issues and resume the flow of workers.

3. Data and empirical strategy

Our data come from 3,512 in-depth household interviews with G2G applicants between August and December of 2018. The first group is the Phase 1 lottery winners, referred to as T1, who won the lottery to migrate and were put in the first phase of intermediation. The second group comprises both Phase 2 and Phase 3 winners, referred to as T2, who won the lottery to migrate but were put into a deferred phase of intermediation. Eventually, this group only received partial (low) intermediation. The third group is the lottery losers, referred to as C, which will serve as the control group. **Figure 2** shows the various steps of the lottery program and the final study sample.

The survey included detailed modules on the migration, labor and earnings of all household members including the applicant and any other migrant members of the household. Interviews were conducted with the applicants themselves if they were present, or with a knowledgeable household member if the applicant was not present. The survey also had modules on household consumption, enterprises, housing and assets, debt position, and female decision-making of the household in Bangladesh. We also collected data on applicant and household characteristics that are unlikely to vary over time, as well as retrospective data on some pre-lottery outcomes.

3.1 Data collection

Constraints on data collection efforts limited the geographic coverage of the survey. Phase 1 winners (group T1) were spread thinly across Bangladesh. BMET limited the number of Phase 1 winners in each village to at most one applicant. Unions, which typically have about 6,000 households from a few villages, had an average of two Phase 1 (group T1) winners. To decrease the geographic scope of data collection efforts, we limited the survey to Dhaka (Mymensingh) and Chittagong Divisions.[8] We then randomly selected 49 of 223 upazilas from these divisions.[9] The survey was conducted in all 522 unions within the selected 49 upazilas.

[8] The Mymensingh Division was formed in 2015, after the G2G lottery program, by combining the northern districts of the Dhaka Division. The survey was conducted in current Dhaka, Mymensingh, and Chittagong divisions.
[9] The data extract we got from BMET had data from applicants in 223 of 258 upazilas. The discrepancy could be a result of the lottery not collecting data from upazilas with very high urban penetration.

In 2011, these divisions housed 53 percent of the entire population, including 48 percent of the rural population (BBS, 2015). These divisions constitute 38 percent of the lottery applicants and 50 percent of the lottery winners. These divisions are also the two most prosperous divisions of Bangladesh. To the extent that migration improves outcomes, the results can be interpreted as a lower-bound of the impact on the entire country.

Sampling strategy and field protocols

The relative scarcity of T1 and the nature of the administrative data we received guided our sampling and field protocols. We received administrative data from BMET in two separate extracts. The first extract was for the lottery losers (control group) which included information on the applicants' names, their parents' names, phone numbers, and the name of their unions. The second extract was the published data on lottery winners (group T1 and T2) which contained the same information except for their phone numbers. We were able to get matched phone numbers for this group from BMT only for 76 percent of group T1 and 16 percent of group T2.

To deal with this, we opted for a combination of phone and field-based tracking of respondents. In each of the sampled unions, enumerators were instructed to find all the T1 individuals. Applicants in the T2 and control groups were randomly ordered, and enumerators were instructed to follow the order in finding respondents. Enumerators would keep going down the randomized order until the number of successful interviews in that group (T2 or control) matched the number of successful interviews in the T1 group. This way, the final survey would have similar sample sizes across treatment groups within each union.

To find the respondents in a sampled union, enumerators first tried calling the applicants for whom we had phone numbers. Each applicant would be called up to five times over the course of several days. If somebody picked up the phone, we also asked if they knew the phone numbers of additional people in the treated groups. Lottery applicants not found by phone were searched in the field. Enumerators would use the information available to locate the respondents. This would include making visits to and consulting with local union officials and asking local residents.

With this protocol, we were able to interview 3,512 lottery applicants, of which 1,127 were Phase 1 winners (group T1), 1,138 were Phase 2 and Phase 3 winners (group T2), and 1,247 were the lottery losers (Control group). We conducted interviews with the applicants themselves if they were present, or with knowledgeable family members if they were absent.

Survey finding rates

The survey finding rate, however, varied by treatment status. We were able to find 94 percent of T1 applicants, 69 percent of T2 applicants, and 68 percent of the control group. Given the scant information we had to locate the applicants, the finding rate of the control group (68 percent) is quite high. For reference, Clemens and Tiongson's (2019) study, which interviews applicants to the Korean EPS migration program in the Philippines based on administrative data, was able to locate and interview only 44 percent of the applicants. The extensive field engagement of the enumerators and, perhaps, the rural setting of Bangladesh, where villagers tend to know about each other, led to the high finding rate in our study.

The almost universal finding rate of the T1 group stems from a few key reasons. First, as the T1 group were required to interact with local officials to prepare for the government intermediation, the local officials were likely to know of them or have updated contact information. Second, winning the lottery made them well-known in the communities and the villagers were also more likely to know them. Third, households with a migrant, particularly international migrants, are more likely to be known in the villages. Given the high desire to migrate internationally in this context, villagers could be more likely to know of international migrants and their families in their village.

This, unfortunately, creates a differential finding rate of 26 percentage points between treatment groups. As explained above, the differential rate reflects the nature of the lottery program and the resulting migration rather than any differences in some underlying economic characteristics. In any case, treating differential finding the same way as differential attrition and estimating bounds (Lee, 2009) resulted in wide confidence intervals for most of the outcomes (except migration and income). Nevertheless, we investigate this issue more deeply in Appendix A.2, and show that under reasonable assumptions the estimates presented in this paper are robust.

Comparison of the sample with the population

Our sample strategy yields a representative sample of the lottery applicants. However, the lottery applicants themselves are a selected sample. For instance, they have a member who is interested in international migration for low-skilled work. They were also expected to finance the migration themselves, albeit at a lower than market cost of migration. This excludes interested applicants who face borrowing constraints to finance migration.

Indeed, as **Appendix Table 1** shows, the study sample is different from a nationally representative household from the Household Income and Expenditure Survey (HIES) of 2016/2017 (BBS, 2017).

To make the comparison similar we successively restrict the HIES sample to rural areas, rural areas in the survey divisions, and further to those with a male member between the ages 20 and 45. As expected, our study samples have a higher propensity to have a migrant and receive remittance income. A quarter of the households in our sample have had a migrant in the past 5 years, compared to 15 percent of the households in the rural sample in the survey provinces and 9 percent nationwide. This translates to the differences in remittance receipts as well. Partly because of remittances, our study sample has higher expenditures and incomes, and lower poverty. The $1.90 poverty rate in our sample is 4 percentage points lower compared to the rural households in survey provinces, and 9 percentage points lower compared to the national rural sample. However, these differences could also reflect the selection of people into the lottery. Our study sample is slightly younger and more educated than other comparable national samples, and more likely to be entrepreneurial. About 44 percent of our sample operate a household business compared to 15-20 percent in comparison samples. Our sample is also more likely to have and operate farmland and also to have taken out a loan in the past year. In addition to the differences in entrepreneurial capacity, these differences may also reflect better access to credit or collateral (farmland) among our sample. This comparison validates that migrants, and potential migrants, have different observable (and potentially unobservable) characteristics than the population. This further casts doubt, as has been pointed out in the literature, on non-experimental estimates of the impact of migration due to the important selection issues.

However, even if the study sample is different from the population at large, our study sample is likely to be representative of the policy-relevant sample: those who would participate in international migration and have some borrowing ability to finance migration.

Balance

Moreover, among the interviewed applicants, time-invariant or retrospective characteristics are balanced across treatment groups. Though we did not have a baseline survey collected before the outcome of the lottery, we collected data on several individual specific characteristics that are unlikely to change over time. We also collected retrospective data on outcomes before the lottery was conducted. As **Table 1** shows, except for a couple of characteristics, most are balanced across treatment groups. Group T1 is 0.22 inches (0.3 percent) taller on average than the control group. Group T2 is 0.16 inches (0.2 percent) taller than the control group. Similarly, group T2 is 2.5 percentage points less likely to be a Muslim, whereas group T1 is 1.5 percentage points more likely to be a Muslim compared to the control group. A joint test across all of these outcomes, however, fails to reject the null that the characteristics are balanced across the lottery outcomes.

The table also shows some characteristics of the lottery applicants. They are 34 years old (29 at the time of lottery) and have 6.8 years of schooling. Three out of five of them were likely to be married at the time of the lottery and lived in household with average size of 5. The average applicant was working more than 11 months in a year at the time of the lottery and earning about Tk 8,800 per-month.

3.2 Empirical strategy

Given the randomized lottery program, we estimate the following specification to study the impact of the lottery (ITT):

$$y_i = \beta_1 T1_i + \beta_2 T2_i + \gamma X_i + \varepsilon_i \tag{1}$$

where y_i is the outcome for applicant i, $T1_i$ and $T2_i$ indicate whether the applicant won the Phase 1 lottery or the Phase 2 and Phase 3 lottery, X_i controls for baseline characteristics, including upazila fixed effects, and ε_i represents the error terms assumed to be clustered at the union level. We weight each observation so that the number of observations within each treatment group is the same within each union. We also present variants of this estimate without the controls, as well as controls reweighted (using inverse probability weights) to balance covariates across treatment arms. Results are robust to these alternative variants.

One concern with an exercise like this one, where we analyze several outcomes, is that some outcomes will be statistically significant purely based on chance. To ensure that our results are not driven by an artifact of our testing multiple outcomes, we present several adjustments to account for multiple inference à la Anderson (2008). First, for each group of outcomes, we construct an inverse-covariance weighted summary index of all outcomes within the family. The summary index is less prone to incorrect inference due to multiple hypotheses testing than the individual outcomes. Second, we control for Family Wise Error Rate (FWER) when we analyze outcomes across families of outcomes. Third, when reporting results for specific outcomes, we control the False Discovery Rate (FDR) and present corrected q-values for the reduced form.

Since the randomized lottery outcomes, particularly T1, do not directly affect outcomes except through migration, we use T1 as an instrument for migration. To estimate the impact of migration on the outcomes, we estimate the following system of equations for the sample that excludes the T2 group:

$$\begin{aligned} y_i &= \delta M_i + \eta X_i + \varepsilon_i \\ M_i &= \alpha T1_i + \xi X_i + \nu_i \end{aligned} \tag{2}$$

where M_i indicates whether the applicant migrated abroad at any point after the initial lottery, and ε_i and ν_i are error terms uncorrelated with each other.

We exclude group T2 for this estimation for potential violation of exclusion restriction. The T2 group was initially offered a delayed government intermediation which did not materialize as planned. It is possible that this group may have taken some steps in expectation of migration in the future, which could have affected the outcomes directly. Furthermore, only a small share of the T2 group received actual intermediation making it only a weak determinant of migration. Hence, we exclude this group to make the interpretation cleaner. However, including this group as another instrument does not qualitatively and substantively change the results.

4. Results and discussion

4.1 Impact of G2G lottery on migration and pre-departure investments

The G2G lottery program was implemented on a large nationwide scale during the registration phase. This modality certainly provided *access* to migration opportunities to interested workers all over Bangladesh. However, it is not clear whether that increase in access translated to an actual act of migration. In this section, we examine whether the desire to migrate, as indicated by a low-cost application to the lottery, translates into the act of migration if given an opportunity. Furthermore, we also investigate whether a credible opportunity to migrate translates into premigration investments that workers could make which could increase their returns from migration.

Impact on migration, intermediation, and current whereabouts

Credible access to migration opportunities translates to actual migration among the applicants. By the time of our survey in 2018, over five years after the lottery, 76 percent of the Phase 1 lottery winners (group T1) had migrated abroad (**Figure 3**). This is 58 percentage points higher than the migration rates in the control group. Most of the T1 migrants, 70 percent of group T1, were intermediated through the government channels. This suggests that, for the large share of applicants, the low-cost application into the lottery program translates to the act of migration when given a credible opportunity. However, as the G2G program started losing steam, it could only intermediate a small share of the Phase 2 and Phase 3 winners (group T2). Still, the migration rate among the T2 group was 10 percentage points higher than that of the control group. The difference between group T2 and the control group comes directly from the G2G intermediation.

The survey migration rates match the migration numbers provided by BMET. Assuming the same migration rate for the entire lottery program, our estimates suggest that about 10,700 would have migrated from the entire pool of 1.43 million applicants. This is only slightly higher than the official count of 9,800 provided by BMET officials in March 2018. This suggests that the rate of government intermediation in our sample is similar to that of the entire program even though we surveyed in divisions closer to the capital.

G2G intermediation led to migrants migrating much earlier than the control group. By the time of our survey, it had been 33 months since the migrants in the control group had migrated. That is, among those in the control group who migrated, they did so about 34 months after the lottery was conducted in February 2013. The T2 group migrated at about the same time as the control group – 33 months after the lottery. The T1 group migrated about 19 months earlier – 15 months after the lottery. Among the G2G migrants, the average T1 (Phase 1 winner) migrant migrated 14 months after the lottery, whereas the average T2 (Phase 2 and 3 winner) migrant migrated 26 months after the lottery. As expected, Malaysia was the most popular destination for the migrants in the T1 and T2 groups because of the nature of the government intermediation. Even without the government intermediation, Malaysia was still the destination for about a quarter of migrants in the control group. In that group, about two-thirds migrated to Gulf countries, including 22 percent going to Saudi Arabia, 21 percent to Oman, and 14 percent to Qatar.

A large share of applicants who migrated are still abroad. About 75 percent of the applicants from group T1 who migrated were still abroad at the time of the survey. The proportion is slightly higher for applicants who migrated from group T2 or the control group, at 78 percent. On average, the time of the survey was almost four years after the initial migration of applicants in group T1. This suggests that these applicants were able to either extend their stay abroad or were able to get another job abroad. Even though the government intermediation was only for one contract term, these migrants were able to use the first migration opportunity to extend the length of their migration episodes.

Impact on investments for migration

We investigate whether the lottery winners take any initiative to better prepare themselves for work abroad. To elicit these investments, we asked applicants whether they made any investments in their language skills, other skills, or their health after the outcome of the lottery and before (any) migration. Such investments could potentially make their lives better in the destination and might also increase their income. **Table 2** shows the results, which are discussed below.

Winning the lottery has a large impact on investments to learn a foreign language, particularly Malay, and take skills training before migration. About 35 percent of group T1 and 9 percent of group T2 invested in foreign language training compared to only 2 percent of the control group. Similarly, 76 percent of group T1 did some skills training compared to 20 percent of group T2 and only 5 percent of the control group. These effects are likely driven by the G2G program requirements (see Appendix A.1), the program does seem to have an impact on increasing preparedness. For instance, the skills training rate in groups T1 and T2 are comparable to the migration rates in those groups (76 percent and 30 percent respectively), that is not so in the case of the control group where 20 percent did eventually migrate.

Not only in the aspects required by the program itself, lottery winners are also more likely to make investments to improve their physical strength, but the higher investments are commensurate with the higher migration rates. Having better physical health could help the migrants adjust to the physically strenuous work abroad or even increase income by improving their productivity or stamina. We do find that lottery winners were more likely than the control group to eat more (nutritious) food, do more exercise, and even take out a gym membership. However, the ratio of these investments to the migration rates were similar for group T1 and the control group, but much higher for group T2. It appears that group T2 overestimated their migration probabilities while making these investment decisions relative to what eventually transpired with the G2G program.

4.2 Impact of lottery and migration on migrants and their households

As seen in the previous section, the lotteries increased migration among the winners, particularly for those in group T1. Since winning the lottery is random, it exogenously increases the migration among the lottery applicants without directly affecting the outcomes.[10] In what follows, we estimate the impact of migration by instrumenting it with winning the lottery and being classified into Phase 1 (group T1). To keep the empirical setup and interpretation cleaner, we drop group T2 from rest of the analysis.

Winning the lottery, and hence migrating abroad, has large impact on a host of outcomes. To analyze the outcomes, we group them into several families of related outcomes. For each family, we create a summary index which is the inverse-covariance weighted average of standardized outcomes within each family. By construction, these indexes have zero mean and standard deviation of 1 in the control

[10] The pre-migration investments made by the migration do not seem to have an effect on the applicants' outcomes after controlling for their current location (or within each location type, for that matter).

group, so the unit of the impact are in standard-deviation units (σ). **Table 3** shows the impact on these summary indexes. To allow inference under multiple hypotheses testing, we present the Family-Wise Error Rate correction on the summary indexes in column (3). The results are robust to multiple-inference concerns.

Winning a lottery increases labor supply and income outcomes of the lottery applicant by over 0.52σ. The IV estimate of the impact of migration on applicant's labor supply and income is 0.89σ. The higher applicant income leads to a higher income measures for the household (by 0.19σ ITT, 0.34σ IV). Household expenditure measure also goes up significantly (by 0.15σ ITT, 0.26σ IV) and so does household assets position (by 0.12σ ITT, 0.21σ IV). The household debt position improves (by 0.12σ ITT, 0.22σ IV) even though many lottery winners borrow money to migrate. Household entrepreneurial activities fall (by 0.11σ ITT, 0.18σ IV) most likely due to the most entrepreneurial member, the applicant, not being present at the household. Household composition also changes in significant ways, particularly through marital outcomes of the applicants and natural split of households from their parent households. Female involvement in household decision making improves drastically (0.29σ ITT, 0.50σ IV) resulting from absence of a male member. Winning the lottery and consequently migration, however, has no impact on measures of household exposure to extreme shocks. This is likely because of noisy data and the lack of power to detect this outcome which occurs rarely in the data.

The Family Wise Error Rate correction method does not change our inference. For instance, there are no impacts on outcomes which are rejected at 95 percent by conventional methods but not after the correction.

In what follows, we unpack the impacts on each family of outcomes and discuss them at a greater detail. We focus on the IV estimate on the discussion, but the tables present ITT estimates from Equation (1) and its variants.

Impact on applicant labor supply and income

Migration leads to substantial gains in incomes for applicants through increased wage-work abroad. Migration itself does not change the total labor supply of the applicants. Even the lottery losers are working 49 hours per week, similar to the lottery winners and migrants. However, unlike non-migrants, who often combine wage work with self-employment and farm work, migrants work almost exclusively in wage-work.

Migration leads to a two to three-fold increase in the income of the applicants. As seen in **Table 4**, we have several measures of income for the applicants. The first measure is retroactive and asks about the applicants' monthly income in 2015, about one year after the migration for group T1.[11] Migration increases this measure by 1.02 log points (178 percent). The second measure directly asks for monthly income in the month preceding the survey. Migration increases this direct measure of income by 0.76 log points (113 percent). The third measure computes income by adding up their wage income, profits from farms and family business, and profits shared among involved household members in proportion to the hours they put in the farm or family business. Migration increases this last measure of income by 0.96 log points (160 percent). However, this last measure is not reported for about a quarter of the applicants that are currently abroad. As group T1 has a larger share of applicants currently abroad, and hence missing income data, estimating the equation without correcting for this will underestimate the gains in income from migration. To overcome such biases, we assume that those currently abroad with missing income earn an income equivalent to the 10th percentile of earnings made by other migrants in the same destination and with similar age, gender, and education profile. Migration increases this measure of income by 1.13 log points (211 percent). Even with the most extreme assumption – that those with missing income data earn zero – migration still increases earnings by 48 percent.[12]

Increase in income is mostly driven by increase in hourly wage rates. Hourly productivity increases by 0.73 log points (107 percent) for our computed measure of income. However, as with the income measure, the hourly productivity measure also suffers from biases due to missing incomes for some migrants. Here as well, we impute incomes for such cases assigning an income equivalent to the 10th percentile of the earnings of migrants in the same destination and have similar age, gender, and education profile. Migration improves this measure of their hourly wage rate by 0.84 log points (131 percent). Even under the most extreme assumption, namely that the individuals with missing income data earn zero, migration improves hourly productivity by 66 percent.

[11] Note that for migrants who are away, the income measures are reported by their household members. Studies have shown that their family members often underestimate migrants' income abroad (Seshan and Zubrickas, 2017). If that is the case in this context as well, then the estimates presented here underestimate the income gains from migration. However, we also asked their monthly income during their migration episode. The reports made by the applicants themselves (if they had returned at the time of the survey) were statistically identical to the reports made by their family members (if applicants were still abroad). This suggests that such misreporting might not be too large in this context.

[12] If migrants with missing income are assumed to have the median earnings of comparable migrants in the same destinations, this increases the income gains from migration to 1.19 log points (230 percent).

Impact on labor supply and income of non-applicant adult household members

The migration of a household member could affect labor supply and income of nonapplicant members in multiple ways. Migration can lead to increased income for the household, which could make the household members consume more leisure, leading to fewer hours of work. Migration also lowers the total supply of labor from the household (domestically). If local labor markets are imperfect, with constraints in hiring, particularly for farming or household business, then the migration of a member could increase the labor supply of the remaining household members. Similarly, migration could increase the reservation wage for the remaining household members, which could lower labor supply, but it would increase productivity (as measured by hourly income).

However, migration has very little impact on various measures of labor supply and income for adult and adult-female household members (**Appendix Table 2** and **Appendix Table 3**). Not only are the impacts statistically insignificant, the point estimate is also small. For instance, none of the estimated impacts exceeds 0.1 standard deviation units. This might be the result of a lot of variability in income and labor supply across households, even in the absence of migration. The large standard errors on the estimated impact are consistent with such high variability.

Impact on income of the household

Consistent with the impacts of migration on the labor supply of both applicant and nonapplicant household members, we find large impacts of migration on household income, driven by the income earned away from the location of the household.

Migration has no impact on the average farm income of the household. As seen above, migration leads to a reduction in total labor supplied in farming by the household (mostly, by the applicants). However, as **Table 5** shows, migration has no impact on net income (profits) from farming. This result seems to be driven by the absence of a risk-taking member from farming. In the control group, households in which the applicant did not migrate had higher average farm income but also a higher variance compared to households in which the applicant did migrate. The pattern holds true in group T1 as well. This suggests that by removing the applicant from farming, migration reduces risk-taking in farming. In fact, migration reduces the probability of a household incurring a loss in farming by 2 percentage points, almost half of the probability in the control group without a migrant applicant. Similarly, migration also reduces the probability of a household making a profit of BDT 50,000 by 6 percentage points, which is a quarter of the probability in the control group households.

Migration lowers household income from nonfarm business by 160 percent, and most of this decline is driven by migrant households not operating nonfarm businesses. This impact is mostly driven by impact at the extensive margin rather than the intensive margin. Migration reduces the probability of a household having a nonfarm business by 12 percentage points (25 percent of the control group mean). With the applicant away, it may have been difficult for group T1 households to maintain an existing household enterprise or to start a new one. Conditional on operating a nonfarm enterprise, however, migration lowers profits by an imprecisely estimated 30 percent. Here as well, having a migrant in the household lowers the probability that the business is operating at a loss, but it does not significantly increase the probability of the profits being in the top 25^{th} percentile.

As expected, migration increases remittance income, and lowers total wage income made at home. This fact is, again, driven by the migrants working for wages abroad rather than at the home location. As a result of high migrant incomes abroad, household remittance income increases several times over. Non-migrant households receive about BDT 16,000 per year on remittances, and migration increases that by more than BDT 82,000. This impact is a combination of extensive and intensive margin. Migration increases the likelihood of a household receiving (or sending) any remittance by 52 percentage points (compared to the control group mean of 21 percent). This suggests that not all migrants remit income back home. It is possible that some remit their income directly to moneylenders to pay back a debt or else save it while abroad. Among the households that receive or send any remittances, migration increases the amount by BDT 59,000 per year. Again, this is only a fraction of the income gains from migration, suggesting that migrants may not remit all of their income back home. However, the amount remitted is higher than the loss in wage income at home. As a result of migration, wage income earned at home falls by about BDT 33,000, much less than the BDT 82,000 households receive in remittance income. Overall, income at home (earned at home plus any remittances) increases by 70 percent upon migration.

Across all income sources, a household doubles its income when a member migrates. Migration substantially increases total income made by all household members. The estimates using logarithm of incomes shows that the increase is over 100 percent.

Impact on household consumption and poverty

The higher income of migrant members, which leads to more income being available in the household, translates to higher per-capita expenditures. As **Table 6** shows, migration significantly improves a wide array of expenditure measures.

Migration increases consumption of food, particularly that of animal proteins. An average non-migrant household in the control group consumes about BDT 33,000 per capita on food and BDT 12,000 per capita on animal proteins (eggs, fish, and meat).[13] Migration raises per-capita expenditures on food by 7 percent and on animal proteins by 17 percent. Animal proteins are both nutritious and more expensive than other food items. Migration increases food consumption of these households, and also changes the food basket toward more expensive and nutritious items.

Health, education, and other nonfood expenditures also increase. About 95 percent of the non-migrant households in the control group have some health expenditures and spend about BDT 5,000 per capita. Migration increases these expenditures by 92 percent. Since migration does not directly affect the health of the household members, we interpret these increases as households receiving better health care. Similarly, per-capita education expenditure also increases by 54 percent, which as we will show later is driven by purchasing better quality education for their children. In addition, non-migrant households in the control group spend about BDT 20,000 per capita on other nonfood expenditures. This measure includes expenditures on regular nonfood items such as clothing, fuel, travel, utilities, household essentials, and minor repairs, but does not include expenditures on larger items (which we examine separately). Migration increases regular nonfood expenditures per capita by 26 percent.

However, consumption of temptation goods remains unchanged. One of the concerns raised over households suddenly earning much higher income, particularly remittance, is that households would spend it on undesirable goods. Generally, it is difficult to classify what those items are, but recent studies have focused on consumption of 'temptation' goods such as cigarettes and alcohol. The consumption of alcohol in Bangladesh is extremely low due to restrictions placed on it. The reported expenditures for cigarettes and related tobacco products are also low, with only 6 percent reporting any expenses. Consequently, we do not find any significant impacts of migration on the consumption of these goods.

Consequently, migration drastically increases the per-capita consumption of household members. Non-migrant households in the control group have a per-capita consumption of BDT 58,000 per year, which increases by 22 percent due to migration.

[13] The consumption also includes the value of home-produced goods.

However, temporary international work migration, given the costs, is not effective at reducing extreme poverty (at PPP$ 1.90 per day). Part of the reason for this is that only 2.2 percent of non-migrant households in the control group were poor by this measure. Though the government intermediation brought down the cost of migration it still cost applicants BDT 45,000, which translates to more than two years of consumption at PPP$ 1.90 per day.[14] Hence, only people who expected to be able to finance this amount applied for the lottery. Many households who were living under the extreme poverty line would be unable to finance the costs of migration and therefore did not apply for the lottery.

But temporary international work migration lowers poverty at higher thresholds. Among non-migrant households in the control group, 27 percent were living under the PPP$ 3.20 per-day threshold and 71 percent were living under the PPP$ 5.50 per-day threshold. Migration reduces poverty rates at these thresholds by 6 percentage points (to 21 percent) and 18 percentage points (to 25 percent).

Migration also increases large and uncommon expenditures, such as on real estate.[15] Migration increases the likelihood of a household purchasing land by 4 percentage points, a 50 percent increase from the rate for non-migrant households in the control group. Similarly, the probability of a migrant household selling land falls by 3 percentage points, again a 33 percent decrease from the rate for non-migrant households in the control group. Consequently, the overall expenditure per-capita in land and housing (purchases as well as major housing repairs) almost doubles. This could explain why the increase in total household income is less than the income gains made from migration – migrants could be saving their earned income in the destination countries to be used for large expenses.

Impact on household assets and quality of houses

As seen in **Table 7**, migration not only improves the expenditures, but also improves the quality of their housing as well as ownership of land and other smaller assets.

Migration leads to the households having an improved quality of dwelling. Migration improves the likelihood of having a dwelling made of permanent materials by 8 percentage points, a 37 percent increase. Similarly, the value of the dwelling was 28 percent higher among migrant households and the

[14] See Shrestha, Mobarak, and Shariff (2019) for more details on how migration under the G2G program compares with that under private channels.

[15] In addition to the regular expenses, we asked households about expenses in less common, but largely consequential, expenditures in the purchase and sale of land and residences. Since only a small proportion of these transactions are captured with a 12 month recall window, we used a 36-month recall window to capture them.

dwelling was more likely to have concrete walls and floors. The probability of the household having a private latrine improves by 11 percentage points from a base of 73 percent.

Migration also increases the likelihood of possession of certain assets more than others. For example, migrant households were more likely to possess fans, mobile phones, jewelry, or stocks, but not more likely to possess other items, such as TVs. Migration reduces the likelihood of households owning a motorcycle, which is explained by the absence of a male member from the household due to migration.

Impact of migration on financial security and household vulnerability

As discussed earlier, the high cost of such low-skilled international migration has been of great policy concern. Most migrants borrow to finance migration and, in the absence of cheaper financing options, resort to moneylenders who charge exorbitant interest rates. Consequently, policymakers and experts in Bangladesh fear that migrants will be debt-ridden even after their return and that the workers will get caught in a debt-migration spiral where they engage in repetitive migration episodes to repay their earlier loans. This could further lead to household vulnerability to various kinds of shocks to their household income.

Contrary to the concerns, we find that (government intermediated) migration reduces household indebtedness, particularly from high-interest sources.[16] As seen in **Table 8**, migration lowers the indebtedness of households despite many of them having borrowed money to migrate.[17] About 73 percent of the non-migrant households in the control group had outstanding loans – migration reduced this by 10 percentage points. Among those who had outstanding loans, migration had no impact on the amount borrowed or the amount of outstanding loans, but it seems to reduce the average interest rates on the loans. The reduction is prominent for loans from local moneylenders (11 percentage points, or 67 percent), NGOs (14 percentage points, or 30 percent), and formal financial institutions (5 percentage points, or 24 percent), whereas there was no impact on the loans taken out from relatives and friends.

A clear pattern emerges from these reductions: the largest (proportional) reductions are from the most expensive credit sources. The average annual interest rate for loans from moneylenders is 58 percent; from NGOs it is 24 percent, and from formal financial institutions it is 22 percent, which are all much

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[16] In Shrestha, Mobarak, and Sharif (2019), we show that the government intermediation also lowered borrowing among applicants who migrated. G2G migrants were less likely to borrow and, when they borrow, do so from cheaper sources compared to non-G2G migrants.

[17] About 70 percent of the G2G migrants borrow to finance their migration.

higher than the average interest rate of 8 percent for loans from friends and relatives. Migration leads to a reduction in indebtedness as well as a shift toward cheaper sources of credit.

Migration also leads toward greater financial security. Migration also makes households more confident about their household finances. The share of households that consider themselves very capable of coming up with BDT 6,300 (about 5 percent of GDP per-capita) in case of need increases by 8 percentage points (28 percent).

However, migration does not affect household vulnerability as measured by incidence of shocks. As **Appendix Table 4** shows, migration has no impact on measures of food insecurity or on the incidence of shocks and related coping strategies. As with the impact on extreme poverty, this result is also potentially driven by the fact that the sample of lottery applicants is not the poorest of Bangladeshi households. It could be that the poorest chose not to participate in the lottery simply because the cost of migration, even under the government intermediation, would be too high for them. For instance, only 2 percent of the non-migrant households in the control group reported that they have to go to bed without enough food. Similarly, only 5 percent of them have had to resort to extreme coping mechanisms (had to borrow food, or eat inadequately, or migrate, or send children to work). About a fifth either did nothing or could use their savings to cope with the shocks.

Impact of migration on household composition

Migration mechanically changes the composition of the household. However, once mechanical factors are incorporated (by either including or excluding them), migration does not change household size (**Appendix Table 5**). Non-migrant households in the control group have 5.7 members, including all migrants, and 4.2 members residing at home (excluding the applicant). Winning the lottery, or migration, does not affect the overall household size. Similarly, migration also does not affect the probability that a household has any nonapplicant migrant members.

However, migration reduces the likelihood of forming new households and having newer members. Because applicants in the treatment group migrated for several years, their families were less likely to split from the households they belonged to at the time of the lottery. That is, migration delays the process of new household formation as applicants (or their spouses) are more likely to cohabitate with their parents or siblings instead of forming their own households. Similarly, migration delays marriage among applicants. Four years after migration, migrants were 6 percentage points (30 percent) less likely to be married than the control group. Consequently, migration lowers the probability of the household having a new member by 13 percentage points (28 percent) and increases the probability that an applicant is still living in the household with an elderly person by 7 percentage points (22 percent). Similarly, the absence of the migrant member means that household headship is likely to be skewed towards their parents or spouses.

Impact of migration on female involvement in decision making

Another aspect of gender-skewed migration such as this is that, in the absence of a key male member, women are disproportionately likely to be involved in managing several aspects of household operations. As **Table 9** shows, female involvement in several measures of household decision-making improves drastically because of male migration. In the survey, we asked about female involvement in making decisions across various dimensions involving children (schooling, childcare), household expenses (expenses in health care, food, clothing, necessities, and managing daily finances), and other large decisions related to household business or entrepreneurial activities (selling household assets, decisions related to farming such as crop/seed choice and fertilizers, decisions related to household debt, and large purchases such as of a house, land, or large appliances).

Female involvement in decision-making improved across all dimensions. Though females were partly involved in making these decisions for about 60 percent of the households in the control group, decisions were made exclusively by female members in only 10 percent of households. Migration increased female involvement in these decisions by 6 percentage points (10 percent) and exclusive female involvement by 13 percent (126 percent). Exclusive female involvement increased by 12 percentage points (43 percent) in matters involving children, by 16 percentage points (193 percent) in matters of household expenses, and by 11 percentage points (213 percent) in matters involving large decisions. That is, migration increases female decision-making in all areas, and disproportionately so in areas where the traditional involvement of females is lower.

Migration mechanically lowers the involvement of the applicant in household decisions. Applicant involvement falls by 27 percentage points (47 percent) across all dimensions. Whereas one could expect the mechanical effects to be larger for regular household decisions and smaller for irregular and large decisions where remote participation of the applicants may be possible, we find the proportional falls to be similar (28–33 percent) across the different dimensions.

Impact of migration on investments on outcomes of the children

When asked about the reasons for migration, migrants frequently bring up child education as one of the key motivations. Migration could increase investments on child human capital in two ways. First, an increase in household income means that the household can purchase more education, or higher quality education, or that the household does not have to rely on children working or performing household chores to free up parental time for economic activities. Second, migration could expose the migrant, and the households, to knowledge about the higher returns to education in domestic as well as foreign labor markets, which would increase investments in schooling as they would value education more.

Migration improves some indicators of child schooling and reduces child labor in wage work. In this context, however, migration affects only certain aspects of child schooling outcomes (**Appendix Table 6** and **Appendix Table 7**). Migration has no impact on the educational attainment, enrollment, or probability of having a private tutor for children ages 5-14 or youths ages 15-24. However, for both demographics, migration increases expenditures in education by 20 to 24 percent. It seems that the higher expenditure is not put toward improving schooling in the extensive margin (even for youths for whom the control group attendance rate is only 42 percent, as opposed to 90 percent for children). Rather, it could be going toward the purchase of inputs (such as school bags) or toward improving the quality of education. Indeed, expenditures are high because of increased expenditures in school fees as well as fees to tutors. This could suggest that families are purchasing better quality schooling through more expensive schools or tutors.

The impacts on educational expenditures reduce any pre-existing gender gaps. The impact on schooling expenditures for children ages 5 to 14 is driven by the impact on girls. Girls in households with a migrant see an increase of 36 percent in educational expenditures, whereas boys only see a modest, and statistically insignificant, improvement of 13 percent. Note that, in this context, girls ages 5 to 14 in Non-migrant households in the control group had 14 percent lower educational expenditure compared to boys. On the other hand, there is no gender difference in the impact of migration on the educational expenditure on youths ages 15 to 24. Unlike the case with younger children, however, there is no gender difference in educational expenditures for youths this age among non-migrant households in the control group either. This suggests that the impact of migration on educational expenditures narrows pre-existing gender gaps.

For children ages 10 to 14, migration also leads to a decline in the probability that a child works for wages; 1.6 percent of children in control group households worked for wages, and this number essentially disappeared for children in the treatment group. The impacts on child wage work do not differ by gender of the child. However, child involvement in farm work is not affected by migration. For the youth, migration does not change their involvement in any type of work activities.

Impact of migration on investments on household entrepreneurial activities

Migration could increase entrepreneurship either through increases in the resources available for such investments or through increases in entrepreneurial knowledge through exposures abroad. However, migration also removes a household member, oftentimes the most entrepreneurial one, from the household, which would lower such investments until the migrants themselves return.

As **Appendix Table 8** shows, the latter channels are likely more important in this context. Migration does not change the probability that a household will have any income from crops. However, among households that do have a crop income, migration leads to a lower likelihood of spending on inputs or hired labor. The probability of having any expenditures on fertilizers fell by 6 percentage points (8 percent); of having any capital expenditures fell by 9 percentage points (13 percent); and of employing an external worker fell by 10 percentage points (15 percent). Migration also does not affect the likelihood of operating a livestock farm nor, if one is operating one, the value of the livestock farm or the likelihood of any expenditure in equipment or hired labor.

However, migration reduces the likelihood that the household operates a nonfarm business. This likelihood falls by 12 percentage points, which is 25 percent of the likelihood in the non-migrant households in the control group. This further suggests that the absence of the applicant, who is likely to be more entrepreneurial among household members, lowers the chances that the household operates a nonfarm enterprise. Conditional on operating an enterprise, the migration of the applicant further lowers the likelihood of hiring an external worker by 12 percentage points (60 percent) and of having capital expenditures by 10 percentage points (13 percent).

If it is the absence of an entrepreneurial member that is behind the lowered entrepreneurial activities, then we can expect those activities to bounce back once the migrant member returns. Further, with greater exposure abroad, along with accumulated financial resources, migration could have a positive impact on entrepreneurship in the longer run. There is some evidence supporting this in the data. For instance, households with a returnee applicant were 11 percentage points more likely to operate a nonfarm family business than households with a non-migrant applicant.

5. Conclusion

This paper shows that government-intermediated international migration is welfare enhancing for the migrants as well as their families even in cases where the migration is explicitly temporary and specifically linked to work in low-skilled manual occupations. Though the full gains for free mobility of labor, à la Clemens (2011), are unlikely to be realized in the current socio-political environment across the world, large welfare gains can still come from opening migration opportunities for low-skilled jobs that natives in richer countries cannot fill. High income countries, as well as upper-middle income countries like Malaysia, can have large developmental impacts by allowing migrant workers from developing countries to fill the excess labor demand in low-skilled jobs though temporary work migration programs.

This paper finds that temporary international migration for low-skilled work almost triples the migrant's earnings. The incomes of the households in Bangladesh more than doubles due to the remittances sent by the migrants. Their families have better living standards and live in better houses and have more assets and durable goods. Even though migrants borrow to finance their migration, they can pay off their debt through their earnings abroad, particularly when cost of migration is lowered, and attain better financial security. These high returns are consistent with the high revealed demand in the developing world for work-related migration opportunities abroad.

Some of the findings in this paper deserve a longer-term follow-up and research. First, the impact on female decision making can be interpreted as being a mechanical impact of the male household member being a migrant. The bigger question is whether this impact will last after the migrants return to join their spouses. Existing evidence, in the context of domestic migration within Bangladesh, is disappointing (Mobarak et al. 2019). However, domestic migration in the context of that study is very short-term, with migrants typically leaving the households for a few weeks to go work in the cities. The longer period of absence and exposure to different cultures abroad on the part of the migrant, and greater agency in financial management for longer duration on the part of the spouses could translate to a more permanent impact in the context of international migration. Second, entrepreneurial activities by the applicant and their households fall in response to migration. This could, again, be mechanically driven by the absence of the most entrepreneurial member of the households. It remains to be seen whether international migration experience and the liquidity, resulting from higher incomes, lead to increased entrepreneurship once they return.

The context of this study highlights the role governments can play to improve access to migration opportunities among the poor. For instance, migration costs were reduced by a factor of seven under the G2G program related to the market cost which allowed those with borrowing constraints to finance migration. Undoubtedly, this had an influence on the high realized welfare gains from migration. Furthermore, the lottery mechanism used to select workers provided migration opportunities to those without social network contacts abroad.[18] Yet, even in this context, the members of the poorest Bangladeshi households did not apply for the lottery program.[19] Borrowing constraints probably prevented the poorest from financing even the reduced cost of migration. Government involvement in intermediation can lower costs among migrants and channel such opportunities towards the poor. But even more needs to be done, perhaps in the form of easier credit access to finance migration, in order for low-skilled international migration to benefit the poorest.

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[18] See Shrestha, Mobarak, and Sharif (2019) for more details on how migration differed under the G2G program compared to private channels.

[19] International extreme poverty (PPP$ 1.90 per day) was only 2.7 percent among the applicants in the control group in our study compared to 15 percent nationwide.

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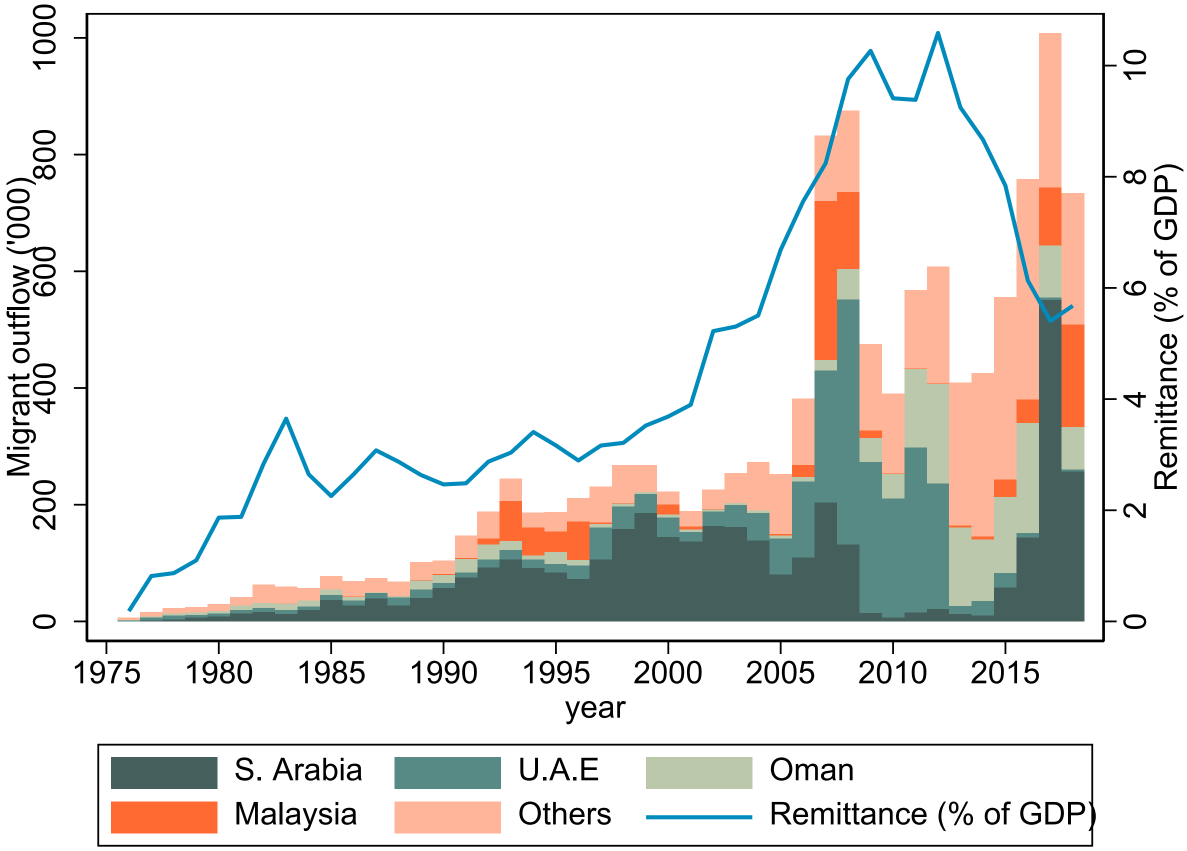
Figures and Tables

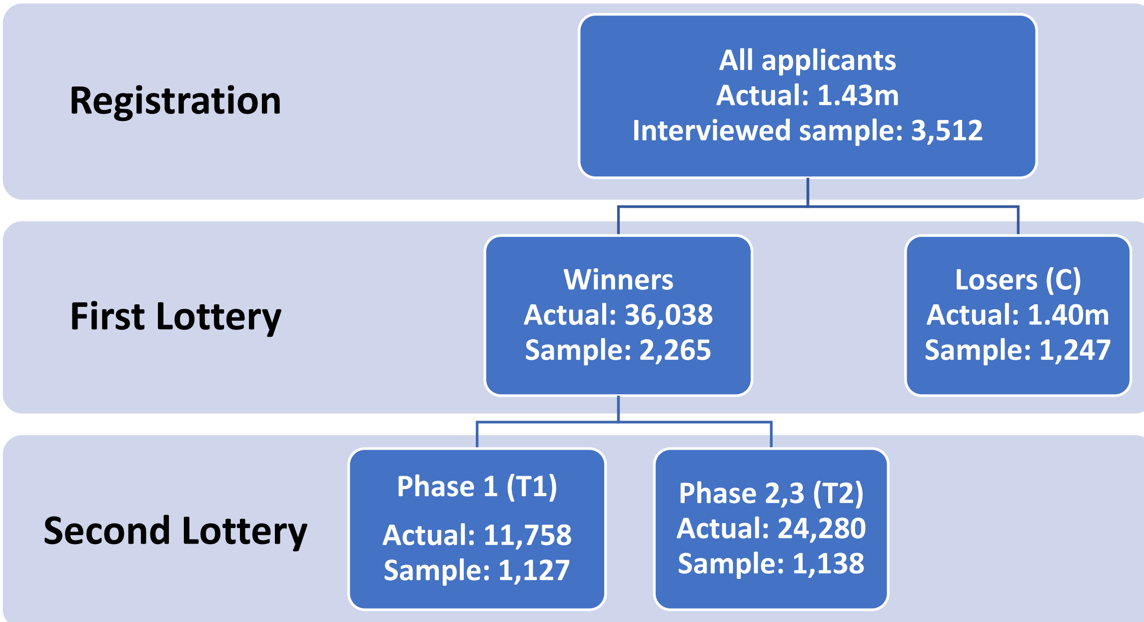
Figures

Figure 1: Migrant outflow for low-skilled work and remittance receipt



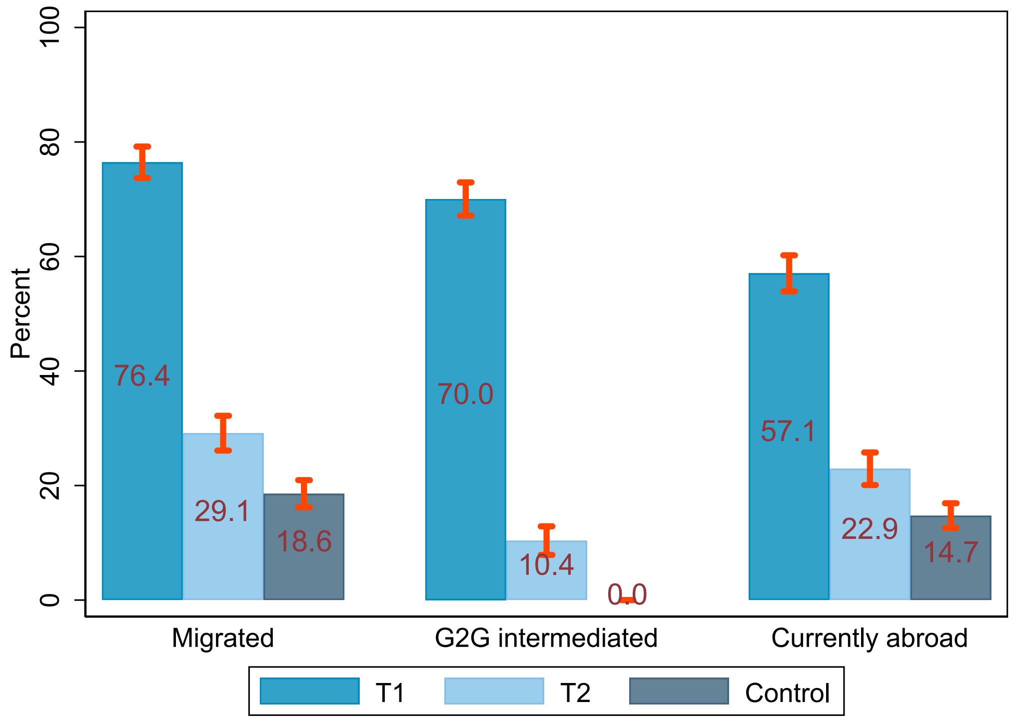
Source: BMET (2019).

Figure 2: Various stages of lottery and study design



Note: Study design.

Figure 3: Impact of winning the lottery on migration



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

Note: Figure shows the impact of winning the lottery on migration. The bar shows the migration rates and the vertical lines denote 95 percent confidence interval.

Tables

Table 1: Balance of characteristics across treatment groups

	(1) C	(2) T1-C	(3) T2-C	(4) T1-T2
Age	34.01***	-0.220	-0.383	0.164
	(0.208)	(0.297)	(0.307)	(0.319)
Height, inches	64.98***	0.220***	0.157**	0.0636
	(0.0545)	(0.0744)	(0.0738)	(0.0815)
Muslim	0.928***	0.0149	-0.0253**	0.0402***
	(0.00785)	(0.00965)	(0.0112)	(0.0108)
Can read and write	0.808***	0.00295	-0.00727	0.0102
	(0.0123)	(0.0160)	(0.0168)	(0.0155)
Completed years of education	6.833***	-0.175	-0.0196	-0.155
	(0.129)	(0.171)	(0.174)	(0.154)
Father is alive	0.588***	-0.00874	-0.00380	-0.00494
	(0.0144)	(0.0212)	(0.0212)	(0.0212)
Father's years of education	3.157***	-0.255	0.157	-0.411**
	(0.125)	(0.161)	(0.169)	(0.176)
Mother is alive	0.835***	-0.00916	0.00380	-0.0130
	(0.0117)	(0.0162)	(0.0165)	(0.0158)
Mother's years of education	1.669***	-0.0749	0.176	-0.251*
	(0.0899)	(0.112)	(0.127)	(0.128)
Married before lottery	0.615***	-0.0164	-0.0241	0.00767
	(0.0141)	(0.0188)	(0.0208)	(0.0206)
HH size before lottery	4.975***	-0.185	-0.170	-0.0152
	(0.0847)	(0.114)	(0.117)	(0.109)
Months worked in 2012	11.37***	-0.0508	0.0492	-0.1000
	(0.0530)	(0.0748)	(0.0706)	(0.0685)
Average monthly income in 2012	8810.1***	565.4	86.65	478.7
	(329.7)	(476.5)	(534.7)	(550.3)
Joint p-value across all outcomes	.	0.225	0.339	0.319

Note: The table shows the relationship between individual characteristics and the treatment status. Each row is estimated from a regression of the characteristics on the treatment indicators controlling for upazila fixed effects and the standard errors are 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.

Table 2: Impact of winning the lottery on investments

	(1) C	(2) T1-C	(3) T2-C	(5) T1-T2
Invest to learn a foreign languag	0.0215***	0.330***	0.0720***	0.258***
	(0.00420)	(0.0162)	(0.0115)	(0.0169)
Invest to learn English	0.0152***	-0.00748*	-0.000621	-0.00686
	(0.00336)	(0.00433)	(0.00480)	(0.00439)
Invest to learn Malay	0.00907***	0.370***	0.0732***	0.297***
	(0.00269)	(0.0160)	(0.0105)	(0.0174)
Invest to learn Arabic	0.0140***	-0.00896**	-0.000331	-0.00863**
	(0.00374)	(0.00414)	(0.00514)	(0.00416)
Invest to learn Hindi	0.00375**	0.000655	-0.000133	0.000787
	(0.00172)	(0.00264)	(0.00253)	(0.00271)
Invest to learn Other language	0.00306	-0.00222	-0.000555	-0.00167
	(0.00194)	(0.00213)	(0.00244)	(0.00168)
Took skills training	0.0531***	0.706***	0.146***	0.561***
	(0.00646)	(0.0174)	(0.0155)	(0.0190)
Ate more food	0.0600***	0.179***	0.126***	0.0530***
	(0.00735)	(0.0156)	(0.0146)	(0.0179)
Ate more protein	0.0730***	0.213***	0.150***	0.0626***
	(0.00777)	(0.0160)	(0.0158)	(0.0181)
Did more exercise	0.0400***	0.111***	0.0827***	0.0286**
	(0.00615)	(0.0136)	(0.0121)	(0.0145)
Took gym membership	0.00310**	0.00691*	0.00234	0.00456
	(0.00156)	(0.00406)	(0.00275)	(0.00439)
Index: Pre-migration investmer	0	0.760***	0.243***	0.518***
	(0.0313)	(0.0488)	(0.0459)	(0.0495)

Note: This table shows the impact of migration on pre-migration outcomes estimated using Equation (1). The column heads show the appropriate comparison along with control group mean. The row indicates the outcome variables. The estimations control for applicant height, age, religion, parental education, and indicators for survey Upazilas. The bottom-most outcome is a covariance-weighted index of all other outcomes in the figure with positive number indicating greater investments. Standard errors, reported in parentheses, are clustered at the union level. *:p>0.1; **: p>0.05; ***: p>0.01

Table 3: Impact of winning the lottery and of migration on index of outcomes

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(6) IV
Index: Labor and Income	0	0.514***	0.517***	0.526***	0.892***
	(0.0331)	(0.0458)	(0.0468)	(0.0453)	(0.0739)
FWER p-value			[0.000]		
Index: HH income	0	0.193***	0.194***	0.189***	0.344***
	(0.0332)	(0.0444)	(0.0467)	(0.0461)	(0.0805)
FWER p-value			[0.000]		
Index: HH consumption	0	0.131***	0.150***	0.153***	0.259***
	(0.0304)	(0.0433)	(0.0448)	(0.0438)	(0.0766)
FWER p-value			[0.004]		
Index: HH condition & asset	0	0.0668	0.122***	0.130***	0.211***
	(0.0309)	(0.0436)	(0.0436)	(0.0427)	(0.0739)
FWER p-value			[0.013]		
Index: Household debt	0	-0.101**	-0.125***	-0.128***	-0.216***
	(0.0300)	(0.0419)	(0.0430)	(0.0422)	(0.0734)
FWER p-value			[0.013]		
Index: Entrepreneurial	0	-0.130***	-0.105***	-0.106***	-0.181***
	(0.0301)	(0.0384)	(0.0398)	(0.0390)	(0.0671)
FWER p-value			[0.024]		
Index: HH Composition	0	0.186***	0.147***	0.146***	0.254***
	(0.0300)	(0.0443)	(0.0431)	(0.0426)	(0.0724)
FWER p-value			[0.004]		
Index: Female decisionmaking	0	0.334***	0.287***	0.294***	0.495***
	(0.0290)	(0.0452)	(0.0466)	(0.0458)	(0.0753)
FWER p-value			[0.000]		
Index: Shock and vulnerability	0	0.00504	-0.00726	-0.00297	-0.0125
	(0.0317)	(0.0422)	(0.0428)	(0.0420)	(0.0725)
FWER p-value			[0.863]		

Note: This table shows the impact of winning the lottery (T1) and of migration on indexes of outcomes estimated using Equations (1) and (2). The first columns show the control group means. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. Each index is covariance-weighted index of a family of outcomes presented in subsequent tables. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (Family Wise Error Rate) FWER adjusted p-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 4: Impact of winning the lottery and of migration on applicant labor and income

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
ihs(Total hours worked)	8.350***	-0.0320	-0.0626	-0.0616	-0.109
	(0.0294)	(0.0470)	(0.0503)	(0.0488)	(0.0863)
FDR q-value			[0.022]		
ihs(Hours in wage work)	5.050***	1.490***	1.225***	1.219***	2.130***
	(0.126)	(0.163)	(0.173)	(0.169)	(0.277)
FDR q-value			[0.001]		
ihs(Hours in farming)	2.877***	-1.474***	-1.354***	-1.344***	-2.337***
	(0.106)	(0.131)	(0.136)	(0.134)	(0.216)
FDR q-value			[0.001]		
ihs(Hours in self-employment)	2.644***	-1.203***	-1.097***	-1.105***	-1.893***
	(0.118)	(0.145)	(0.149)	(0.146)	(0.241)
FDR q-value			[0.001]		
ihs(monthly income in 2015)	9.659***	0.570***	0.596***	0.592***	1.022***
	(0.0390)	(0.0524)	(0.0561)	(0.0547)	(0.0937)
FDR q-value			[0.001]		
ihs(income last month, direct)	9.205***	0.520***	0.437***	0.433***	0.758***
	(0.0901)	(0.124)	(0.131)	(0.129)	(0.219)
FDR q-value			[0.001]		
ihs(monthly income, computed)	11.83***	0.593***	0.536***	0.519***	0.957***
	(0.0691)	(0.0912)	(0.0963)	(0.0977)	(0.164)
FDR q-value			[0.001]		
ihs(monthly inc, computed -- p10)	11.88***	0.714***	0.657***	0.649***	1.133***
	(0.0673)	(0.0854)	(0.0897)	(0.0869)	(0.147)
FDR q-value			[0.001]		
ihs(hourly income, computed)	3.757***	0.406***	0.406***	0.409***	0.726***
	(0.0290)	(0.0422)	(0.0433)	(0.0426)	(0.0710)
FDR q-value			[0.001]		
ihs(hourly income, computed -- p10)	3.789***	0.484***	0.483***	0.483***	0.837***
	(0.0288)	(0.0401)	(0.0415)	(0.0402)	(0.0645)
FDR q-value			[0.001]		
Index: Labor and Income	0	0.514***	0.517***	0.526***	0.892***
	(0.0331)	(0.0458)	(0.0468)	(0.0453)	(0.0739)

Note: This table shows the impact of winning the lottery (T1) and of migration on labor and income of the applicant estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 5: Impact of winning the lottery and of migration on household income

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
ihs(Farm income)	8.371***	0.111	0.159	0.168	0.275
	(0.162)	(0.211)	(0.218)	(0.214)	(0.371)
FDR q-value			[0.130]		
ihs(Non-farm business income)	5.131***	-1.099***	-0.887***	-0.927***	-1.530***
	(0.182)	(0.230)	(0.243)	(0.238)	(0.406)
FDR q-value			[0.001]		
ihs(Rental and other income)	5.233***	-0.129	-0.0908	-0.103	-0.157
	(0.151)	(0.199)	(0.206)	(0.202)	(0.349)
FDR q-value			[0.171]		
ihs(Remittance income)	2.379***	4.675***	4.362***	4.389***	7.520***
	(0.186)	(0.273)	(0.293)	(0.285)	(0.444)
FDR q-value			[0.001]		
ihs(Labor income, home)	5.191***	-1.555***	-1.557***	-1.560***	-2.685***
	(0.174)	(0.238)	(0.250)	(0.248)	(0.419)
FDR q-value			[0.001]		
ihs(Labor income, away)	4.891***	3.759***	3.679***	3.700***	7.011***
	(0.202)	(0.305)	(0.310)	(0.305)	(0.493)
FDR q-value			[0.001]		
ihs(Labor inc., away --p10)	5.194***	4.247***	4.053***	4.082***	7.192***
	(0.198)	(0.279)	(0.284)	(0.277)	(0.421)
FDR q-value			[0.001]		
ihs(Total income, all sources)	12.51***	0.538***	0.568***	0.580***	1.083***
	(0.0789)	(0.0931)	(0.0912)	(0.0870)	(0.166)
FDR q-value			[0.001]		
ihs(Total income -- p10)	12.54***	0.602***	0.612***	0.603***	1.085***
	(0.0786)	(0.0991)	(0.0997)	(0.0958)	(0.168)
FDR q-value			[0.001]		
Index: HH income	0	0.193***	0.194***	0.189***	0.344***
	(0.0332)	(0.0444)	(0.0467)	(0.0461)	(0.0805)

Note: This table shows the impact of winning the lottery (T1) and of migration on income aggregated at the household level estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 6: Impact of winning the lottery and of migration on household consumption and poverty

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Log(food per capita)	10.26***	0.0344	0.0386*	0.0429*	0.0664*
	(0.0168)	(0.0221)	(0.0226)	(0.0220)	(0.0383)
FDR q-value			[0.072]		
Log(protein per capita)	9.076***	0.0789**	0.0886***	0.0960***	0.153***
	(0.0282)	(0.0326)	(0.0334)	(0.0324)	(0.0568)
FDR q-value			[0.013]		
Log(non-food exp. per capita)	9.681***	0.122***	0.136***	0.138***	0.235***
	(0.0196)	(0.0280)	(0.0290)	(0.0287)	(0.0496)
FDR q-value			[0.001]		
Log(health exp. per capita)	7.118***	0.346***	0.378***	0.375***	0.653***
	(0.0637)	(0.0883)	(0.0908)	(0.0885)	(0.156)
FDR q-value			[0.001]		
Log(education exp. per capita)	4.153***	0.197	0.249**	0.257**	0.431**
	(0.0823)	(0.125)	(0.125)	(0.124)	(0.212)
FDR q-value			[0.051]		
Log(tobacco per capita)	-1.076***	0.138*	0.109	0.0926	0.188
	(0.0539)	(0.0733)	(0.0807)	(0.0803)	(0.137)
FDR q-value			[0.093]		
Log(Consumption per capita)	10.83***	0.106***	0.116***	0.119***	0.200***
	(0.0168)	(0.0222)	(0.0230)	(0.0228)	(0.0396)
FDR q-value			[0.001]		
Poverty rate ($1.90 per day)	0.0266***	-0.00559	-0.00730	-0.00699	-0.0126
	(0.00463)	(0.00629)	(0.00674)	(0.00662)	(0.0115)
FDR q-value			[0.117]		
Poverty rate ($3.20 per day)	0.267***	-0.0324*	-0.0314*	-0.0323*	-0.0542*
	(0.0135)	(0.0175)	(0.0184)	(0.0183)	(0.0313)
FDR q-value			[0.072]		
Poverty rate ($5.50 per day)	0.701***	-0.0924***	-0.103***	-0.105***	-0.178***
	(0.0143)	(0.0197)	(0.0200)	(0.0196)	(0.0343)
FDR q-value			[0.001]		
Bought real-estate	0.0819***	0.0269**	0.0246*	0.0268**	0.0425*
	(0.00768)	(0.0123)	(0.0130)	(0.0126)	(0.0221)
FDR q-value			[0.058]		
Sold real-estate	0.112***	-0.0200	-0.0195	-0.0189	-0.0337
	(0.00933)	(0.0131)	(0.0142)	(0.0139)	(0.0242)
FDR q-value			[0.093]		
ihs(Large exp. per capita)	2.024***	0.667**	0.580**	0.687**	1.001**
	(0.187)	(0.261)	(0.274)	(0.267)	(0.465)
FDR q-value			[0.044]		
Index: HH consumption	0	0.131***	0.150***	0.153***	0.259***
	(0.0304)	(0.0433)	(0.0448)	(0.0438)	(0.0766)

Note: This table shows the impact of winning the lottery (T1) and of migration on household consumption and poverty estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 7: Impact of winning the lottery and of migration on household conditions and assets

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Pakka or semi-pakka dwelling	0.216***	0.0386**	0.0477***	0.0472***	0.0822***
	(0.0131)	(0.0175)	(0.0177)	(0.0172)	(0.0299)
FDR q-value			[0.014]		
Log(value of dwelling(s))	11.65***	0.106**	0.144***	0.151***	0.248***
	(0.0355)	(0.0463)	(0.0466)	(0.0456)	(0.0793)
FDR q-value			[0.009]		
# rooms in dwelling	2.634***	0.0306	0.0852	0.0838	0.147
	(0.0445)	(0.0586)	(0.0566)	(0.0561)	(0.0958)
FDR q-value			[0.077]		
Cement walls	0.215***	0.0365**	0.0467***	0.0461***	0.0805***
	(0.0132)	(0.0176)	(0.0179)	(0.0174)	(0.0303)
FDR q-value			[0.015]		
Cement floor	0.294***	0.0312	0.0469**	0.0462**	0.0808**
	(0.0147)	(0.0191)	(0.0193)	(0.0189)	(0.0328)
FDR q-value			[0.019]		
Has private latrine	0.727***	0.0530***	0.0648***	0.0659***	0.112***
	(0.0136)	(0.0188)	(0.0189)	(0.0186)	(0.0323)
FDR q-value			[0.007]		
ihs(value of land)	13.46***	0.204	0.298**	0.325**	0.514**
	(0.0935)	(0.129)	(0.134)	(0.134)	(0.226)
FDR q-value			[0.024]		
has TV	0.500***	-0.0186	0.00300	0.00294	0.00517
	(0.0168)	(0.0186)	(0.0192)	(0.0188)	(0.0326)
FDR q-value			[0.208]		
# fans per capita	0.500***	0.0365**	0.0445***	0.0458***	0.0769***
	(0.0118)	(0.0157)	(0.0148)	(0.0146)	(0.0252)
FDR q-value			[0.009]		
# mobile per capita	0.502***	0.00505	0.00954	0.00877	0.0165
	(0.00983)	(0.0131)	(0.0123)	(0.0122)	(0.0209)
FDR q-value			[0.206]		
has Motorcycle or scooter	0.359***	-0.0417**	-0.0291	-0.0262	-0.0502
	(0.0156)	(0.0193)	(0.0202)	(0.0198)	(0.0342)
FDR q-value			[0.077]		
Bought stock, jewellery, etc	0.0858***	0.0164	0.0201	0.0215	0.0346
	(0.00854)	(0.0130)	(0.0134)	(0.0131)	(0.0227)
FDR q-value			[0.077]		
Index: HH condition & asset	0	0.0668	0.122***	0.130***	0.211***
	(0.0309)	(0.0436)	(0.0436)	(0.0427)	(0.0739)

Note: This table shows the impact of winning the lottery (T1) and of migration on household conditions and assets estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 8: Impact of winning the lottery and of migration on household debt

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Any loan	0.734***	-0.0484**	-0.0551***	-0.0541***	-0.0949***
	(0.0131)	(0.0192)	(0.0203)	(0.0197)	(0.0345)
FDR q-value			[0.017]		
ihs(amount borrowed)	11.67***	-0.0652	-0.0829	-0.0933	-0.152
	(0.0473)	(0.0753)	(0.0788)	(0.0778)	(0.142)
FDR q-value			[0.186]		
ihs(outstanding loan)	11.22***	0.0843	0.0890	0.0728	0.160
	(0.0517)	(0.0808)	(0.0839)	(0.0831)	(0.147)
FDR q-value			[0.186]		
Average annual interest rate	21.37***	-3.803*	-3.638*	-4.347**	-6.632*
	(1.577)	(1.996)	(2.097)	(2.007)	(3.740)
FDR q-value			[0.101]		
Loans from NGO	0.434***	-0.0725***	-0.0793***	-0.0794***	-0.137***
	(0.0154)	(0.0201)	(0.0214)	(0.0213)	(0.0364)
FDR q-value			[0.001]		
Loans from friends	0.352***	0.0196	0.00353	0.00506	0.00610
	(0.0143)	(0.0194)	(0.0210)	(0.0207)	(0.0357)
FDR q-value			[0.462]		
Loans from Banks/MFI	0.215***	-0.0243	-0.0290*	-0.0349**	-0.0500*
	(0.0132)	(0.0170)	(0.0176)	(0.0173)	(0.0298)
FDR q-value			[0.000]		
Loans from Moneylender	0.174***	-0.0551***	-0.0645***	-0.0624***	-0.111***
	(0.0117)	(0.0142)	(0.0147)	(0.0145)	(0.0251)
FDR q-value			[0.001]		
Loan to others	0.00695***	0.00389	0.00420	0.00455	0.00725
	(0.00247)	(0.00410)	(0.00392)	(0.00377)	(0.00667)
FDR q-value			[0.186]		
Can easily get 6,300 Taka	0.274***	0.0320*	0.0456**	0.0466**	0.0786**
	(0.0134)	(0.0183)	(0.0195)	(0.0187)	(0.0330)
FDR q-value			[0.032]		
Index: Household debt	0	-0.101**	-0.125***	-0.128***	-0.216***
	(0.0300)	(0.0419)	(0.0430)	(0.0422)	(0.0734)

Note: This table shows the impact of winning the lottery (T1) and of migration on household debt positions estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Table 9: Impact of winning the lottery and of migration on household decision-making

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Female: all matters	0.597***	0.0464***	0.0354**	0.0356**	0.0610**
	(0.0105)	(0.0147)	(0.0153)	(0.0151)	(0.0256)
FDR q-value			[0.009]		
Only female: all matters	0.106***	0.0878***	0.0778***	0.0814***	0.134***
	(0.00587)	(0.00987)	(0.0100)	(0.00995)	(0.0161)
FDR q-value			[0.001]		
Female: child matters	0.836***	-0.00206	-0.00705	-0.00639	-0.0121
	(0.00887)	(0.0125)	(0.0131)	(0.0128)	(0.0223)
FDR q-value			[0.070]		
Only female: child matters	0.293***	0.0829***	0.0724***	0.0762***	0.125***
	(0.0106)	(0.0147)	(0.0152)	(0.0149)	(0.0252)
FDR q-value			[0.001]		
Female: big decisions	0.513***	0.0530***	0.0420**	0.0418**	0.0724**
	(0.0119)	(0.0165)	(0.0170)	(0.0167)	(0.0283)
FDR q-value			[0.007]		
Only female: big decisions	0.0498***	0.0690***	0.0615***	0.0642***	0.106***
	(0.00515)	(0.00923)	(0.00910)	(0.00902)	(0.0150)
FDR q-value			[0.001]		
Female: HH expense related	0.595***	0.0611***	0.0476***	0.0479***	0.0820***
	(0.0125)	(0.0172)	(0.0179)	(0.0177)	(0.0299)
FDR q-value			[0.005]		
Only female: HH expense related	0.0825***	0.104***	0.0922***	0.0966***	0.159***
	(0.00688)	(0.0122)	(0.0124)	(0.0124)	(0.0199)
FDR q-value			[0.001]		
Applicant: all matters	0.573***	-0.173***	-0.156***	-0.158***	-0.268***
	(0.0109)	(0.0155)	(0.0158)	(0.0154)	(0.0245)
FDR q-value			[0.001]		
Index: Female decisionmaking	0	0.334***	0.287***	0.294***	0.495***
	(0.0290)	(0.0452)	(0.0466)	(0.0458)	(0.0753)

Note: This table shows the impact of winning the lottery (T1) and of migration on female involvement in household decisions estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix A.1: Description of the G2G intermediation process

The following steps provide an outline of the G2G intermediation process.[1]

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 A.2: Survey finding rates

Survey finding rates

With the field protocol described in Section 3, we were able to find and interview a higher share of T1 group compared to T2 and the control group. As **Appendix Figure 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.[1] 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.

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 9**).

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 9** 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 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 9** 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. (2014). 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. Behaghel et al. (2014) 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 Behaghel et al (2014) approach to construct bounds (BCGL bounds, hereafter) in our context as well. Columns 2 and 3 of **Appendix Table 10** 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 Behaghel at al 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 10**. 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.

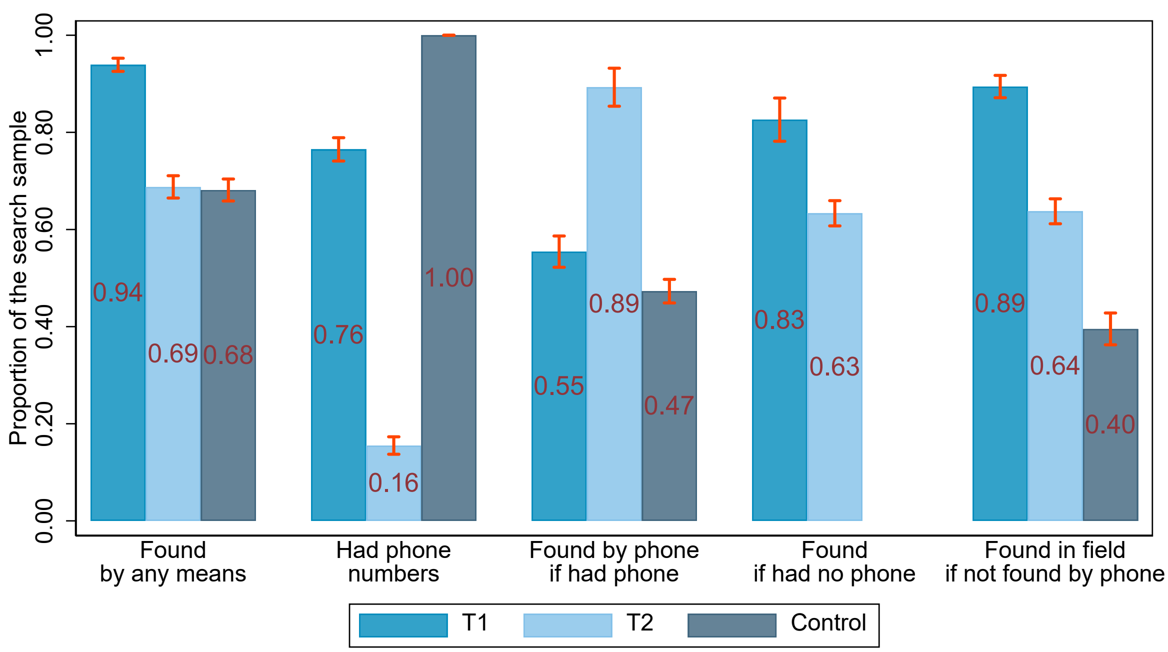
Lastly, we resort to a pragmatic approach to characterize the likelihood of large bias due to differential finding rates. We assume that the higher finding rate of the treatment group is due to the artifact of winning the lottery and not some underlying characteristics that could directly affect the 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 10** reports the proportion of the simulations in which we fail to reject the null of no effect. As seen in the table, for outcomes on migration, labor and income measures, per-capita consumption, and female-decision making, we do not fail to reject the null in any of the simulations. Even for other key outcomes, the proportion is fairly low. This shows that, for the key outcomes, any biases due to differential finding rates are extremely unlikely.

Finally, in **Appendix Table 11**, we restrict the sample to unions with similar finding rates between the treatment and the control groups. This essentially restricts the sample to cases where the control group finding rates are high. In columns 2-4, we restrict the sample to unions where the finding rates are equal across treatment groups. This reduces the sample by almost a third but has a finding rate of 96 percent in both groups. But the ITT estimates are similar to the rest of the sample with tighter Lee bounds. In columns 5-7, we restrict the sample to unions where the finding rates are within 25 percentage points of each other. The ITT estimates in this sample are also similar to the full sample, and, due to low differential attrition, have tighter Lee bounds. This further shows the robustness of our key results to differential attrition.

Appendix A.3: Additional Figures and Tables

Appendix Figures

Appendix Figure 1: Survey finding rates



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

Appendix Tables

Appendix Table 1: Comparison of the study sample with the population

	Study sample	HIES 2016 All	Rural	… in survey divisions	… with adult male
	(1)	(2)	(3)	(4)	(5)
Any migrant, last 5 years	.249	.0869***	.101***	.149***	.0743***
	[.433]	[.282]	[.302]	[.356]	[.262]
Any remittance income last year	.25	.0287***	.0329***	.0503***	.0196***
	[.433]	[.167]	[.178]	[.219]	[.139]
Per-capita consumption	58584	55204***	48722***	54578***	50811***
	[41205]	[50120]	[44742]	[42423]	[35836]
Poverty rate (PPP$1.90 per day)	.0266	.0953***	.117***	.066***	.0767***
	[.161]	[.294]	[.322]	[.248]	[.266]
Poverty rate (PPP$3.20 per day)	.267	.43***	.503***	.394***	.434***
	[.443]	[.495]	[.5]	[.489]	[.496]
Per-capita income	54944	57120	47411***	50851*	49639**
	[64826]	[187182]	[111078]	[112414]	[63115]
Average age of household members	26.1	29.1***	29.6***	28.7***	25.1***
	[10.9]	[12.5]	[13.1]	[12.8]	[8.44]
Average years of adult education	5.9	4.5***	3.95***	4.1***	4.48***
	[3.18]	[3.88]	[3.48]	[3.51]	[3.38]
Household size	4.93	4.07***	4.12***	4.23***	4.63***
	[2.14]	[1.61]	[1.64]	[1.68]	[1.64]
Operates Non-farm business	.436	.179***	.164***	.156***	.191***
	[.496]	[.383]	[.37]	[.363]	[.393]
Farming Household	.858	.558***	.689***	.599***	.604***
	[.349]	[.497]	[.463]	[.49]	[.489]
Took loan in past year	.734	.302***	.332***	.28***	.317***
	[.442]	[.459]	[.471]	[.449]	[.465]

Note: This table shows the comparison of the study sample with the Bangladeshi population. The first column presents the mean and standard deviations for the control group in the study sample. Column 2 represents the statistics for the nationally representative Household Income and Expenditure Survey of 2016/2017. 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. The significance stars in columns 2-5 test whether the means are significantly different from the study sample. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 2: Impact of winning the lottery and of migration on non-applicant adult labor and income

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
ihs(Total hours worked)	5.008***	0.114	0.0861	0.0923	0.149
	(0.0785)	(0.101)	(0.104)	(0.103)	(0.179)
FDR q-value			[1.000]		
ihs(Hours in wage work)	0.703***	0.0111	0.0246	0.0267	0.0425
	(0.0482)	(0.0696)	(0.0711)	(0.0711)	(0.122)
FDR q-value			[1.000]		
ihs(Hours in farming)	3.750***	0.102	0.0554	0.0674	0.0957
	(0.0777)	(0.107)	(0.108)	(0.105)	(0.185)
FDR q-value			[1.000]		
ihs(Hours in self-employment)	0.581***	0.0225	0.0269	0.0224	0.0466
	(0.0469)	(0.0667)	(0.0697)	(0.0681)	(0.120)
FDR q-value			[1.000]		
ihs(monthly income in 2015)	7.414***	-0.0677	-0.0785	-0.0900	-0.135
	(0.0605)	(0.0852)	(0.0909)	(0.0873)	(0.155)
FDR q-value			[1.000]		
ihs(income last month, direct)	5.028***	-0.0308	0.0367	0.0148	0.0632
	(0.121)	(0.154)	(0.164)	(0.161)	(0.279)
FDR q-value			[1.000]		
ihs(monthly income, computed)	6.948***	0.196	0.174	0.181	0.300
	(0.111)	(0.149)	(0.154)	(0.152)	(0.265)
FDR q-value			[1.000]		
ihs(monthly inc, computed -- p10)	6.969***	0.196	0.174	0.181	0.301
	(0.110)	(0.149)	(0.154)	(0.152)	(0.265)
FDR q-value			[1.000]		
ihs(hourly income, computed)	2.921***	-0.0642	-0.0329	-0.0419	-0.0577
	(0.0404)	(0.0565)	(0.0599)	(0.0591)	(0.104)
FDR q-value			[1.000]		
ihs(hourly income, computed -- p10)	2.921***	-0.0642	-0.0329	-0.0419	-0.0577
	(0.0404)	(0.0565)	(0.0599)	(0.0591)	(0.104)
FDR q-value			[1.000]		
Index: Adult labor and income	0	-0.0155	-0.0112	-0.00905	-0.0193
	(0.0291)	(0.0359)	(0.0397)	(0.0394)	(0.0676)

Note: This table shows the impact of winning the lottery (T1) and of migration on labor and income of non-applicant adults in the households estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 3: Impact of winning the lottery and of migration on non-applicant adult female labor and income

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
ihs(Total hours worked)	5.008***	0.114	0.0861	0.0923	0.149
	(0.0785)	(0.101)	(0.104)	(0.103)	(0.179)
FDR q-value			[1.000]		
ihs(Hours in wage work)	0.703***	0.0111	0.0246	0.0267	0.0425
	(0.0482)	(0.0696)	(0.0711)	(0.0711)	(0.122)
FDR q-value			[1.000]		
ihs(Hours in farming)	3.750***	0.102	0.0554	0.0674	0.0957
	(0.0777)	(0.107)	(0.108)	(0.105)	(0.185)
FDR q-value			[1.000]		
ihs(Hours in self-employment)	0.581***	0.0225	0.0269	0.0224	0.0466
	(0.0469)	(0.0667)	(0.0697)	(0.0681)	(0.120)
FDR q-value			[1.000]		
ihs(monthly income in 2015)	7.414***	-0.0677	-0.0785	-0.0900	-0.135
	(0.0605)	(0.0852)	(0.0909)	(0.0873)	(0.155)
FDR q-value			[1.000]		
ihs(income last month, direct)	5.028***	-0.0308	0.0367	0.0148	0.0632
	(0.121)	(0.154)	(0.164)	(0.161)	(0.279)
FDR q-value			[1.000]		
ihs(monthly income, computed)	6.948***	0.196	0.174	0.181	0.300
	(0.111)	(0.149)	(0.154)	(0.152)	(0.265)
FDR q-value			[1.000]		
ihs(monthly inc, computed -- p10)	6.969***	0.196	0.174	0.181	0.301
	(0.110)	(0.149)	(0.154)	(0.152)	(0.265)
FDR q-value			[1.000]		
ihs(hourly income, computed)	2.921***	-0.0642	-0.0329	-0.0419	-0.0577
	(0.0404)	(0.0565)	(0.0599)	(0.0591)	(0.104)
FDR q-value			[1.000]		
ihs(hourly income, computed -- p10)	2.921***	-0.0642	-0.0329	-0.0419	-0.0577
	(0.0404)	(0.0565)	(0.0599)	(0.0591)	(0.104)
FDR q-value			[1.000]		
Index: Adult labor and income	0	-0.0155	-0.0112	-0.00905	-0.0193
	(0.0291)	(0.0359)	(0.0397)	(0.0394)	(0.0676)

Note: This table shows the impact of winning the lottery (T1) and of migration on labor and income of non-applicant female adults in the households estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 4: Impact of winning the lottery and of migration on incidence of household shocks and vulnerability

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Not enough food	0.0231***	0.000881	-0.00218	-0.00226	-0.00376
	(0.00448)	(0.00620)	(0.00607)	(0.00603)	(0.0103)
FDR q-value			[1.000]		
Any shock	0.438***	0.0160	0.0216	0.0217	0.0372
	(0.0161)	(0.0198)	(0.0210)	(0.0205)	(0.0356)
FDR q-value			[1.000]		
Number of shocks	0.541***	-0.0112	0.000503	0.000679	0.000868
	(0.0229)	(0.0269)	(0.0288)	(0.0285)	(0.0488)
FDR q-value			[1.000]		
Extreme coping measures	0.0516***	0.00165	-0.00292	-0.000849	-0.00503
	(0.00670)	(0.00965)	(0.00967)	(0.00944)	(0.0164)
FDR q-value			[1.000]		
Easy coping measures	0.196***	0.00961	0.0166	0.0164	0.0286
	(0.0124)	(0.0156)	(0.0163)	(0.0159)	(0.0276)
FDR q-value			[1.000]		
Extreme coping, Natural shocks	0.0790***	-0.0296	-0.0162	0	-0.0230
	(0.0287)	(0.0309)	(0.0399)	(.)	(0.0471)
FDR q-value			[1.000]		
Extreme coping, crop shocks	0.0562***	0.0222	0.0151	0	0.0235
	(0.0200)	(0.0379)	(0.0397)	(.)	(0.0526)
FDR q-value			[1.000]		
Extreme coping, health shocks	0.124***	0.00126	-0.0165	-0.0143	-0.0279
	(0.0180)	(0.0272)	(0.0265)	(0.0256)	(0.0423)
FDR q-value			[1.000]		
Index: Shock and vulnerability	0	0.00504	-0.00726	-0.00297	-0.0125
	(0.0317)	(0.0422)	(0.0428)	(0.0420)	(0.0725)

Note: This table shows the impact of winning the lottery (T1) and of migration on household shocks and vulnerability estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 5: Impact of winning the lottery and of migration on household composition

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
HH size, incl migrants	5.692***	0.0473	0.0983	0.0995	0.170
	(0.0751)	(0.102)	(0.0875)	(0.0873)	(0.148)
FDR q-value			[0.130]		
HH size, excl. appl. + migrants	4.222***	0.0396	0.0944	0.0976	0.163
	(0.0643)	(0.0907)	(0.0797)	(0.0796)	(0.135)
FDR q-value			[0.130]		
Has non-applicant migrant	0.295***	0.0100	0.00909	0.00938	0.0157
	(0.0141)	(0.0192)	(0.0192)	(0.0190)	(0.0326)
FDR q-value			[0.298]		
HH split since 2013	0.132***	-0.0388***	-0.0319**	-0.0316**	-0.0550**
	(0.00966)	(0.0134)	(0.0130)	(0.0128)	(0.0220)
FDR q-value			[0.026]		
Has new HH member since 2013	0.460***	-0.0658***	-0.0742***	-0.0730***	-0.128***
	(0.0161)	(0.0196)	(0.0202)	(0.0197)	(0.0342)
FDR q-value			[0.001]		
Married since 2013	0.189***	-0.0299*	-0.0332**	-0.0335**	-0.0572**
	(0.0114)	(0.0163)	(0.0167)	(0.0165)	(0.0283)
FDR q-value			[0.065]		
# children	1.630***	-0.0533	-0.0247	-0.0185	-0.0427
	(0.0366)	(0.0467)	(0.0475)	(0.0479)	(0.0807)
FDR q-value			[0.298]		
# elderly 65+	0.339***	0.0256	0.0429*	0.0422*	0.0741*
	(0.0165)	(0.0236)	(0.0243)	(0.0237)	(0.0413)
FDR q-value			[0.079]		
HH head: applicant	0.507***	-0.236***	-0.222***	-0.224***	-0.383***
	(0.0156)	(0.0205)	(0.0206)	(0.0201)	(0.0324)
FDR q-value			[0.001]		
HH head: wife	0.0937***	0.143***	0.139***	0.139***	0.240***
	(0.00872)	(0.0147)	(0.0149)	(0.0146)	(0.0240)
FDR q-value			[0.001]		
HH head: parent	0.359***	0.0480**	0.0379*	0.0395**	0.0653*
	(0.0143)	(0.0202)	(0.0204)	(0.0201)	(0.0346)
FDR q-value			[0.074]		
Index: HH Composition	0	0.186***	0.147***	0.146***	0.254***
	(0.0300)	(0.0443)	(0.0431)	(0.0426)	(0.0724)

Note: This table shows the impact of winning the lottery (T1) and of migration on household composition estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 6: Impact of winning the lottery and of migration on outcomes of children aged 5-14

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Years of schooling	2.947***	-0.125	-0.127	-0.166	-0.219
	(0.0804)	(0.116)	(0.121)	(0.119)	(0.205)
FDR q-value			[0.522]		
Attends school	0.902***	0.000434	-0.00271	-0.00436	-0.00467
	(0.00908)	(0.0134)	(0.0147)	(0.0142)	(0.0250)
FDR q-value			[0.944]		
Has school uniform	0.883***	0.00237	0.00691	0.00534	0.0119
	(0.0116)	(0.0155)	(0.0153)	(0.0151)	(0.0257)
FDR q-value			[0.944]		
Has school-bag	0.841***	0.0278*	0.0411**	0.0377**	0.0705***
	(0.0128)	(0.0162)	(0.0162)	(0.0157)	(0.0273)
FDR q-value			[0.098]		
Has private tutor	0.579***	0.0103	0.0146	0.0111	0.0251
	(0.0179)	(0.0237)	(0.0252)	(0.0246)	(0.0426)
FDR q-value			[0.944]		
Log(Total education expenditure)	8.701***	0.0838*	0.109**	0.100**	0.188**
	(0.0350)	(0.0483)	(0.0511)	(0.0492)	(0.0867)
FDR q-value			[0.098]		
Works in farm	0.0422***	-0.00210	-0.00407	-0.0000328	-0.00698
	(0.0115)	(0.0152)	(0.0142)	(0.0132)	(0.0235)
FDR q-value			[0.944]		
Works for wage	0.0157***	-0.0150**	-0.0144**	-0.0154**	-0.0247**
	(0.00595)	(0.00605)	(0.00634)	(0.00656)	(0.0106)
FDR q-value			[0.098]		
Works in self-employment	0.00741**	0.00725	0.0103	0.00925	0.0176
	(0.00318)	(0.00732)	(0.00856)	(0.00727)	(0.0142)
FDR q-value			[0.479]		
Index: Child (age 5-14) outcomes	0	0.0453	0.0461	0.0382	0.0794
	(0.0325)	(0.0412)	(0.0423)	(0.0412)	(0.0717)

Note: This table shows the impact of winning the lottery (T1) and of migration on outcomes of children aged 5-14 estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 7: Impact of winning the lottery and of migration on outcomes of youth aged 15-24

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Years of schooling	8.703***	-0.125	-0.00327	0.0211	-0.00589
	(0.101)	(0.153)	(0.159)	(0.156)	(0.280)
FDR q-value			[1.000]		
Attends school	0.424***	0.00203	0.000555	0.000580	0.000999
	(0.0177)	(0.0276)	(0.0279)	(0.0272)	(0.0492)
FDR q-value			[1.000]		
Has private tutor	0.565***	0.0175	0.0217	0.0352	0.0353
	(0.0267)	(0.0376)	(0.0398)	(0.0374)	(0.0616)
FDR q-value			[1.000]		
Log(Total education expenditure)	9.542***	0.132**	0.131**	0.128**	0.212**
	(0.0404)	(0.0564)	(0.0588)	(0.0544)	(0.0919)
FDR q-value			[0.205]		
Worked last month	0.385***	-0.0180	-0.0204	-0.0170	-0.0367
	(0.0178)	(0.0250)	(0.0261)	(0.0252)	(0.0459)
FDR q-value			[1.000]		
Works in farm	0.229***	-0.0148	-0.0157	-0.0148	-0.0283
	(0.0160)	(0.0229)	(0.0237)	(0.0227)	(0.0420)
FDR q-value			[1.000]		
Works for wage	0.0781***	-0.00134	-0.00305	-0.00107	-0.00551
	(0.00957)	(0.0136)	(0.0138)	(0.0138)	(0.0244)
FDR q-value			[1.000]		
Works in self-employment	0.0779***	-0.00235	-0.00231	-0.00173	-0.00416
	(0.00954)	(0.0132)	(0.0138)	(0.0136)	(0.0243)
FDR q-value			[1.000]		
Index: Youth (age 15-24) outcomes	0	0.0413	0.0640	0.0649	0.115
	(0.0374)	(0.0521)	(0.0537)	(0.0521)	(0.0941)

Note: This table shows the impact of winning the lottery (T1) and of migration on outcomes of youth aged 15-24 estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 8: Impact of winning the lottery and of migration on entrepreneurial activities

	(1) Control group	(2) ITT	(3) ITT (Controls)	(4) ITT (IPW)	(5) IV
Has crop income	0.737***	-0.0245	-0.0122	-0.0125	-0.0211
	(0.0134)	(0.0174)	(0.0181)	(0.0177)	(0.0307)
FDR q-value			[0.327]		
Has fertilizer expense	0.746***	-0.0284	-0.0354	-0.0337	-0.0595*
	(0.0163)	(0.0213)	(0.0220)	(0.0215)	(0.0358)
FDR q-value			[0.148]		
Has capital expenditure for crop	0.738***	-0.0496**	-0.0554**	-0.0524**	-0.0931***
	(0.0167)	(0.0213)	(0.0221)	(0.0216)	(0.0357)
FDR q-value			[0.035]		
Hired workers for crop	0.682***	-0.0581**	-0.0620**	-0.0585**	-0.104***
	(0.0176)	(0.0232)	(0.0241)	(0.0235)	(0.0393)
FDR q-value			[0.035]		
Has Livestock	0.788***	-0.000481	-0.00511	-0.00256	-0.00881
	(0.0118)	(0.0166)	(0.0170)	(0.0164)	(0.0288)
FDR q-value			[0.467]		
ihs(livestock value)	10.01***	-0.127	-0.141	-0.140	-0.236
	(0.0680)	(0.0916)	(0.0979)	(0.0956)	(0.161)
FDR q-value			[0.165]		
Has capital expenditure for livestock	0.378***	-0.0130	-0.0204	-0.0232	-0.0340
	(0.0181)	(0.0202)	(0.0209)	(0.0206)	(0.0340)
FDR q-value			[0.310]		
Hired workers for livestock	0.00531**	0.00453	0.00475	0.00444	0.00791
	(0.00220)	(0.00413)	(0.00522)	(0.00517)	(0.00854)
FDR q-value			[0.310]		
Has non-farm business	0.436***	-0.0833***	-0.0691***	-0.0720***	-0.119***
	(0.0148)	(0.0189)	(0.0198)	(0.0193)	(0.0330)
FDR q-value			[0.004]		
ihs(business value)	11.38***	-0.00121	0.0417	0	0.0795
	(0.0846)	(0.141)	(0.145)	(.)	(0.265)
FDR q-value			[0.467]		
Has capital expenditure for business	0.792***	-0.0355	-0.0545*	0	-0.102*
	(0.0176)	(0.0277)	(0.0300)	(.)	(0.0540)
FDR q-value			[0.104]		
Hired workers for business	0.197***	-0.0505*	-0.0636**	0	-0.119**
	(0.0185)	(0.0264)	(0.0273)	(.)	(0.0497)
FDR q-value			[0.039]		
Index: Entrepreneurial	0	-0.130***	-0.105***	-0.106***	-0.181***
	(0.0301)	(0.0384)	(0.0398)	(0.0390)	(0.0671)

Note: This table shows the impact of winning the lottery (T1) and of migration on household entrepreneurial activities estimated using Equation (2). The first column shows the control group mean. Column (2) shows the ITT estimates with only Upazila indicators, Column (3) adds other controls (applicant height, age, religion, and parental education). Column (4) presents the estimate of the reduced form with inverse-probability-weights (IPW) estimated using the controls. Column (5) presents the 2-SLS estimates of the impact of migration. The rows indicate the outcome variables. *ihs* refers to the inverse-hyperbolic sine transformation of the variables. The bottom most outcome is a covariance-weighted index of all other outcomes with positive values representing increased income and labor supply. Standard errors, reported in parentheses, are clustered at the union level. Column (3) also presents the (False Discovery Rate) FDR adjusted q-values that adjust for multiple-hypotheses testing. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 9: Lee bounds on ITT estimates accounting for differential finding rates

	Full sample	Lee bounds (full sample)		Lee bounds (phone sample)	
	(1)	(2)	(3)	(4)	(5)
	ITT	Lower bound	Upper bound	Lower bound	Upper bound
Migrated abroad	0.571***	0.483***	0.806***	0.611***	0.782***
	(0.017)	(0.022)	(0.012)	(0.026)	(0.045)
Index: Labor and Income	0.486***	0.053	1.007***	0.359***	0.873***
	(0.047)	(0.056)	(0.048)	(0.080)	(0.083)
ihs(monthly income, computed)	0.721***	0.280***	1.391***	0.463***	1.310***
	(0.089)	(0.103)	(0.078)	(0.151)	(0.117)
Index: HH income	0.197***	-0.298***	0.623***	-0.014	0.393***
	(0.045)	(0.048)	(0.053)	(0.089)	(0.089)
ihs(Total income, all sources)	0.554***	0.174	1.054***	0.671***	0.749***
	(0.104)	(0.110)	(0.087)	(0.139)	(0.179)
Index: HH consumption	0.157***	-0.276***	0.643***	-0.146*	0.406***
	(0.043)	(0.049)	(0.044)	(0.081)	(0.080)
Log(Consumption per capita)	0.120***	-0.151***	0.361***	-0.066	0.236***
	(0.023)	(0.025)	(0.028)	(0.042)	(0.045)
Index: HH condition & asset	0.062	-0.415***	0.505***	-0.197**	0.345***
	(0.043)	(0.047)	(0.051)	(0.078)	(0.077)
Log(value of dwelling(s))	0.100**	-0.447***	0.679***	-0.193**	0.394***
	(0.049)	(0.055)	(0.058)	(0.094)	(0.095)
Index: Household debt	-0.095**	-0.548***	0.262***	-0.374***	-0.060
	(0.042)	(0.044)	(0.048)	(0.065)	(0.066)
Any loan	-0.052***	-0.171***	0.208***	-0.110***	0.062
	(0.019)	(0.025)	(0.029)	(0.033)	(0.043)
Index: Shock and vulnerability	-0.004	-0.623***	0.231***	-0.626***	0.081
	(0.043)	(0.037)	(0.054)	(0.051)	(0.067)
Index: Female decisionmaking	0.288***	-0.263***	0.749***	-0.059	0.522***
	(0.045)	(0.047)	(0.052)	(0.084)	(0.084)
Index: HH Composition	0.177***	-0.282***	0.722***	-0.054	0.514***
	(0.044)	(0.055)	(0.047)	(0.083)	(0.079)
Index: Entrepreneurial	-0.113***	-0.543***	0.359***	-0.542***	0.114
	(0.041)	(0.042)	(0.050)	(0.091)	(0.073)

Note: This table shows non-parametric Lee bounds to address the differential finding rate. Column 1 shows the ITT estimate (unweighted) for reference. 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>0.1; **: p>0.05; ***: p>0.01

Appendix Table 10: Behaghel et al bounds on ITT estimates and simulation results

	Full Sampl	BCGL bounds (phone sample)		BCGL bounds (full sample)		Simulations
	(1)	(2)	(3)	(4)	(5)	(6)
	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
	(0.017)	(0.029)	(0.024)	(0.022)	(0.030)	
Index: Labor and Income	0.486***	0.523***	0.655***	0.450***	0.500***	0.000000
	(0.047)	(0.072)	(0.071)	(0.057)	(0.063)	
ihs(monthly income, computed)	0.721***	0.667***	0.826***	0.707***	0.755***	0.000000
	(0.089)	(0.148)	(0.139)	(0.099)	(0.101)	
Index: HH income	0.197***	0.158**	0.314***	0.184***	0.228***	0.000077
	(0.045)	(0.072)	(0.083)	(0.059)	(0.052)	
ihs(Total income, all sources)	0.554***	0.668***	0.788***	0.554***	0.592***	0.000000
	(0.104)	(0.117)	(0.111)	(0.095)	(0.095)	
Index: HH consumption	0.157***	-0.010	0.140*	0.154***	0.195***	0.000068
	(0.043)	(0.079)	(0.075)	(0.052)	(0.059)	
Log(Consumption per capita)	0.120***	0.079*	0.159***	0.100***	0.121***	0.000000
	(0.023)	(0.044)	(0.040)	(0.030)	(0.030)	
Index: HH condition & asset	0.062	-0.009	0.156**	0.004	0.053	0.033993
	(0.043)	(0.080)	(0.079)	(0.061)	(0.060)	
Log(value of dwelling(s))	0.100**	-0.042	0.128	0.066	0.108	0.008904
	(0.049)	(0.089)	(0.085)	(0.067)	(0.066)	
Index: Household debt	-0.095**	-0.143**	0.019	-0.139***	-0.073	0.077932
	(0.042)	(0.068)	(0.082)	(0.054)	(0.058)	
Any loan	-0.052***	-0.076*	0.010	-0.056**	-0.041	0.018813
	(0.019)	(0.040)	(0.029)	(0.022)	(0.034)	
Index: Shock and vulnerability	-0.004	-0.067	0.056	-0.013	0.071	0.999987
	(0.043)	(0.063)	(0.073)	(0.054)	(0.061)	
Index: Female decisionmaking	0.288***	0.181**	0.378***	0.267***	0.313***	0.000000
	(0.045)	(0.078)	(0.092)	(0.065)	(0.057)	
Index: HH Composition	0.177***	0.118	0.294***	0.163**	0.222***	0.016546
	(0.044)	(0.087)	(0.079)	(0.066)	(0.067)	
Index: Entrepreneurial	-0.113***	-0.213**	-0.058	-0.088	-0.042	0.133138
	(0.041)	(0.101)	(0.063)	(0.062)	(0.058)	

Note: This table shows non-parametric Lee bounds to address the differential finding rate. Column 1 shows the ITT estimate (unweighted) for reference. Columns 2 and 3 shows the Behaghel et al. (2014) 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 Behaghel et al (2014) bounds on the full sample using a mix of phone call attempts and a measure of union population as the truncating instrument. 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. *:p>0.1; **: p>0.05; ***: p>0.01

Appendix Table 11: Lee bounds on various sampling restrictions

	Full sample	Unions with equal finding rate			Differential finding rate <.25		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ITT	ITT	Lower bound	Upper bound	ITT	Lower bound	Upper bound
Sample size	2832	1003			1165		
Finding rate (treatment)	0.939	0.960			0.943		
Finding rate (control)	0.681	0.960			0.923		
Migrated abroad	0.571***	0.551***	0.551***	0.552***	0.551***	0.546***	0.566***
	(0.017)	(0.027)	(0.027)	(0.029)	(0.025)	(0.026)	(0.028)
Index: Labor and Income	0.486***	0.445***	0.237***	0.638***	0.442***	0.266***	0.602***
	(0.047)	(0.071)	(0.085)	(0.086)	(0.066)	(0.082)	(0.081)
ihs(monthly income, computed)	0.721***	0.717***	0.702***	0.717***	0.640***	0.640***	0.861***
	(0.089)	(0.139)	(0.234)	(0.145)	(0.133)	(0.137)	(0.169)
Index: HH income	0.197***	0.255***	0.094	0.430***	0.224***	0.089	0.375***
	(0.045)	(0.068)	(0.078)	(0.081)	(0.064)	(0.079)	(0.079)
ihs(Total income, all sources)	0.554***	0.488***	-0.103	0.909***	0.465***	-0.101	0.870***
	(0.104)	(0.160)	(0.126)	(0.185)	(0.144)	(0.117)	(0.167)
Index: HH consumption	0.157***	0.169***	0.162**	0.177**	0.147**	0.102	0.206***
	(0.043)	(0.065)	(0.074)	(0.085)	(0.061)	(0.070)	(0.074)
Log(Consumption per capita)	0.120***	0.153***	0.143***	0.159***	0.128***	0.092**	0.153***
	(0.023)	(0.035)	(0.043)	(0.038)	(0.033)	(0.040)	(0.037)
Index: HH condition & asset	0.062	0.095	0.073	0.120	0.061	0.018	0.094
	(0.043)	(0.065)	(0.076)	(0.080)	(0.061)	(0.079)	(0.071)
Log(value of dwelling(s))	0.100**	0.155**	0.141*	0.162*	0.130*	0.076	0.176**
	(0.049)	(0.077)	(0.085)	(0.090)	(0.072)	(0.088)	(0.084)
Index: Household debt	-0.095**	-0.007	-0.014	-0.003	-0.051	-0.114	-0.016
	(0.042)	(0.064)	(0.088)	(0.073)	(0.061)	(0.075)	(0.061)
Any loan	-0.052***	-0.050*	-0.050*	-0.049	-0.040	-0.047*	-0.025
	(0.019)	(0.030)	(0.030)	(0.031)	(0.028)	(0.028)	(0.030)
Index: Shock and vulnerability	-0.004	0.029	0.028	0.038	0.053	-0.030	0.066
	(0.043)	(0.064)	(0.065)	(0.101)	(0.061)	(0.076)	(0.062)
Index: Female decisionmaking	0.288***	0.371***	0.366***	0.375***	0.395***	0.348***	0.441***
	(0.045)	(0.068)	(0.073)	(0.076)	(0.063)	(0.074)	(0.073)
Index: HH Composition	0.177***	0.242***	0.233***	0.266***	0.249***	0.214***	0.324***
	(0.044)	(0.067)	(0.072)	(0.082)	(0.062)	(0.070)	(0.076)
Index: Entrepreneurial	-0.113***	-0.141**	-0.541***	-0.140**	-0.128**	-0.508***	-0.083
	(0.041)	(0.063)	(0.063)	(0.069)	(0.059)	(0.062)	(0.069)

Note: This table shows non-parametric Lee bounds for sub-samples of the data. Column 1 shows the ITT estimate (unweighted) for reference. Columns 2-4 restricts the sample to unions where the treatment and the control group had same finding rate. Column 2 presents the ITT estimates on this subsample. Columns 3 and 4 presents the Lee bounds in this sub-sample. Columns 5-7 restrict the sample to unions where the differential finding rate is less than 25 percentage points. Column 5 presents the ITT for this subsample. Columns 6 and 7 presents the Lee bounds on this sub-sample. *:p>0.1; **: p>0.05; ***: p>0.01.

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