Remitting Religiosity: Evidence of International Migrants Changing Norms in Their Home Country*

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Abstract

This paper investigates whether international migration increases religiosity in the home country. Using a neighborhood-level leave-one-out fraction of migrant households as an instrument, I find that the migration of a household member from Bangladesh to a Muslim majority country increases the likelihood that a male child of that household is sent to a religious school. This result is robust to potential concerns of exclusion restriction violation and minor relaxation of strict exogeneity assumption. I find that the rise in religious schooling is driven by an increase in religiosity through international migration and can reduce the returns to international migration.

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Keywords: International migration, labor migration, social remittances, religiosity, Islam, religious schooling, madrasa, human capital, and Bangladesh.

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"Migration to the Middle East—conventionally understood to be the site of authentic Islam—has exposed Bangladeshi workers to alternative ways of being and acting like Muslims. Many return with new ideals about what it means to be a good, authentic Muslim …." (Siddiqi, 2006)

1 Introduction

International migrants can transfer "social remittances"—norms, culture, and institutions—from their host country (the country of a migrant's destination) to their home country (the country of a migrant's origin).[1] Social remittances may have a significant effect on the socio-economic behavior of a migrant household (a household that sends a migrant abroad for work but lives in the home country).

This paper addresses the question of whether international migration can affect religiosity in the home country through social remittances when the dominant religion of the host country and the home country is the same. If religion has a strong presence in the social and political lives of people in the host country, a migrant might channel newly obtained norms back to the home country.

I examine whether external migration increases religiosity in the home country by estimating the causal impact of a migrant from Bangladesh going to a Muslim-majority country on the likelihood of a migrant household sending a child to an Islamic school, commonly known as a *madrasa*. Bangladeshis value madrasa education for its teaching of Arabic and the Quran (Rao and Hossain, 2011), and households sometimes chose madrasas over public or private secular non-madrasa schools. Bangladesh is also a major exporter of manpower (United Nations, Department of Economic and Social Affairs, Population Division, 2017). These conditions make Bangladesh an ideal setting for this study.

Using the 2010 round of the Bangladesh Household Income and Expenditure Survey (HIES), I find that sending a migrant to a Muslim-majority country increases madrasa schooling of male children of the migrant household. In particular, I find that sending a migrant to a Muslim-majority country increases a household's propensity to send a male

[1] I borrow the term from the sociology literature (see Levitt, 1998; Levitt and Lamba-Nieves, 2011)

child to a madrasa, while no such effect exists when the household has a migrant in a Muslim-minority country.

Migration increases madrasa schooling at the expense of a reduction in enrollment in non-madrasa schools as migration does not increase overall schooling. In addition, this result is driven by an increase in the extensive margin of madrasa education at the household-level as there is a significant positive effect of migration to a Muslim majority country on the likelihood of a migrant household sending at least one male child to a madrasa.

I use the leave-one-out fraction of migrant households in the primary sampling units (PSUs)—that is, the concentration of migrant households among the neighbors of a household—as an instrument and exploit the within sub-district variation of the instrument to causally identify the effect of a household sending an external migrant on the likelihood of that household sending a child to a madrasa. As there are two endogenous migration variables, I use two instrumental variables—the PSU-level leave-one-out fraction of households with a migrant in a Muslim-majority country and the PSU-level leave-one-out fraction of households with a migrant in a Muslim-minority country. As I am using an instrumental variable approach, my estimates are local average treatment effects.

The identification assumption is that while the within sub-district variation of the concentration of migrant households among neighbors across PSUs is a strong predictor of a household's likelihood of sending a migrant abroad, it does not directly influence a household's choice of school for its children. The instrumental variable I use is similar in spirit to that used by Fruehwirth et al. (2019) to estimate the causal impact of religiosity on depression, where they exploited the within-school variation of average peer religiosity across cohorts.

The instrumental variables are relevant and do not suffer from the weak instrument problem. The first-stage coefficients of the instrumental variables are significant. I also implement a weak instrument test following Olea and Pflueger (2013) and can rule out the concern that the instruments are weak.

To defend the validity of the instrument, I decompose the exclusion restriction into two parts following the strategy of Fruehwirth et al. (2019)—an individual-specific component and a PSU-specific component. The former component might cause a violation of the exclusion restriction if a household makes a strategical change of location to facilitate external migration. The PSU-specific component might compromise the identification assumption if PSU-level unobservables that vary within the sub-district are correlated with the instruments.

Using the existing literature and robustness tests, I argue that a violation of the exclusion restriction through either of the two components of the error terms is unlikely, and, therefore, that the validity of my identification strategy is not threatened. Evidence about migration in developing countries in general and Bangladesh in particular suggests that the violation of the exclusion restriction through individual-level components is implausible. Migration is a costly endeavor, and credit constraints limit the migration of households in Bangladesh (Bryan et al., 2014; Mendola, 2008). On the other hand, the causal estimates are robust to the inclusion of the PSU-level leave-one-out average of control and outcome variables in the main specification, suggesting that PSU-level confounding variables are unlikely to compromise the validity of the exclusion restriction either.

The findings are also robust when I allow a minor relaxation of the strict exogeneity assumption following Conley et al. (2012). Under the plausible exogeneity assumption of Conley et al. (2012), the instrumental variables can enter the second stage with a nonzero coefficient. I follow Nunn and Wantchekon (2011) and Azar et al. (2017) to make assumptions about the values of the coefficients of the instrumental variables. Imposing bounds on the coefficients of the instrumental variables, I calculate the bounds of the coefficients of a household having a migrant in a Muslim-majority country under plausible exogeneity. My findings remain robust if there is a very small correlation between the instruments and the error term in the second stage.

I find similar results when I use the 2016 round of the HIES, suggesting that the estimates are intertemporally valid. Estimates using the 2016 round of the HIES show that the magnitude of the impact on the madrasa schooling of male children does not change and that the likelihood of female children being sent to madrasas increases. While a rise in the school enrollment can explain why the madrasa education of female children increased, there is no change in the enrollment of male children—not unlike the main results I obtain using the HIES 2010. This indicates that, over time, the increase in madrasa schooling as a result of migration has not faded; rather, it has likely intensified.

I rule out an income effect and learning channel as plausible mechanisms and show that an increase in religiosity through social remittances is the most plausible mechanism of the rise in religiosity. As madrasas are cheaper than non-madrasa options, an income effect is not consistent with the findings. Learning about Muslim-majority countries might inspire households to send children to madrasas more from the belief that the skills learned at the madrasa (e.g., speaking Arabic) or merely the signaling value of having a madrasa education would help them migrate in the future. However, the quality of education at the madrasas does not enable students to learn Arabic properly. In addition, the signaling value of madrasa education in Muslim-majority countries also seems inconsistent as citizens from countries such as India, the Philippines, and Sri Lanka have a significant presence and earning potential in these countries (Naufal, 2011; World Bank, 2019).

As madrasa education is of religious nature and madrasa graduates have poorer labor market outcomes, finding only causal impacts for migrant households of the Islamic faith and who have more than median household-level income suggests that it is a change in religiosity through social remittances that drives the increase in madrasa schooling. The social remittance mechanism makes economic sense too. As madrasa schooling is negatively associated with learning and labor market outcomes (Asadullah and Chaudhury, 2010; Asadullah et al., 2009) and madrasa-educated working-age males are more likely to be out of labor market and unemployed, these findings mean that wealthier households can afford to choose to perform a religious activity by sending a male child to a madrasa while forgoing the potential future income gain of a non-religious education.

It is important to note that the specific finding here is context dependent. In other contexts, where the host country and the home country have different religions or the role that religion plays in the collective lives of the people of the two countries differ, similar results might not hold in a different context, limiting the external validity.

This paper makes three major contributions. First, it adds to the understanding of how migration can influence norms and institutions by establishing a causal link between international migration and religiosity in the home.[2] While there are direct effects of international

[2]See Forrester et al. (2019) for a review of the literature that explores the effects of international migration

migration on education (Antman, 2011, 2012; Theoharides, 2018), human capital formation (Dinkelman and Mariotti, 2016), and labor market outcomes (Binzel and Assaad, 2011; Nguyen and Winters, 2011), the existing literature also shows how international migration facilitates a transfer of political institutions (Batista et al., 2019; Batista and Vicente, 2011; Chauvet et al., 2016; Chauvet and Mercier, 2014; Mercier, 2016; Pfutze, 2012; Spilimbergo, 2009; Tuccio et al., 2019), a transfer of conservative norms (Tuccio and Wahba, 2018)[3], a change in fertility norms (Beine et al., 2013), and a reduction in widespread social practices such as female genital mutilation (Diabate and Mesplé-Somps, 2019) in the home country. However, to the best of my knowledge, this is the first study that establishes a causal relationship between international migration and religiosity of the home country.

Second, this paper contributes to the literature that examines the returns to migration. International migration increases migrants' income (Clemens, 2013; McKenzie et al., 2010), who remit money to the home country (Yang, 2008). Remittance income plays a significant role in reducing poverty (Adams and Cuecuecha, 2013; Adams and Page, 2005) and child labor (Cuadros-Menaca and Gaduh, 2019), and in increasing human capital formation (Ambler et al., 2015; Yang, 2008) in the home country. By establishing a causal relationship between international migration and madrasa education, this paper finds that the returns to migration may be overestimated if social remittances are unaccounted for.

Third, this paper provides an economic justification to improve the quality of madrasa education in Bangladesh. As it stands, with more migration, the economy loses future productivity due to the rise in the number of poorly trained madrasa students. This might also increase inequality as madrasa students will face an adverse labor market situation compared to their peers in the non-madrasa schools.

The remainder of the paper is organized as follows. Section 2 provides a detailed background of madrasa education in Bangladesh, followed by a discussion of the data and the descriptive statistics in Section 3. Section 4 covers the empirical strategy and identification. The results and robustness checks are presented in Section 5. Section 6 concludes the paper.

on the norms and institutions of the host country.

[3]Conservative norms might also increase in an importing country through international trade (see Autor et al., 2016).

2 Background

Primary and secondary education in Bangladesh has three major streams—Bengali-medium schools that follow the national curriculum, English-medium schools that largely follow a British curriculum, and madrasas. The primary focus of teaching in madrasas is religion. They teach the Quran, hadith, and other religious lessons.

There are two kinds of madrasas in Bangladesh that provide primary education or above is provided—Qawmi and Alia. Alia madrasas operate under the supervision of the state's madrasa education board and follow the national curriculum set by the board. The first Alia madrasa, known as the Calcutta Madrasa, was established in Bengal by the British colonial rulers to provide a model institution for Muslims which would teach both religious and secular subjects. Though the Calcutta Madrasa moved to Dhaka after the partition of India, it was not until the early 1980s that Alia madrasas began to spread in Bangladesh. Enrollment in registered secondary madrasas in Bangladesh grew by 45% from 1998 to 2014 (Asadullah and Chaudhury, 2016). The curriculum of Alia madrasas includes religious subjects such as the Quran, Islamic jurisprudence, and the Arabic language as well as secular subjects such as the Bengali and English languages, math, science, and the like.

Qawmi madrasahs, on the other hand, are operated by non-governmental entities, are mostly community based, depend on their own assets and charities for funding, and follow their own curriculum. Qawmi madrasas began operating in South Asia during the Mughal period (Asadullah et al., 2009). After the British colonized the sub-continent in the 18th century, these madrasas stopped receiving state support, turned away from teaching secular subjects, and focused only on the teaching of religion. They still exist in Bangladesh and often have an influence in politics and policy due to their organization and obedience to hierarchy. A Qawmi madrasa might offer non-religious teaching at its own discretion (and probably depending on its ability to hire teachers). Degrees offered by Qawmi madrasas were not recognized by the state until 2017.

The pattern of enrollment in madrasas and the location of madrasas suggest that the decision to send a child to a madrasa in Bangladesh is unlikely to be due to supply-side factors and is more likely to be influenced by demand-side factors such as poverty, cost, or preference.

Most of the madrasa-enrolled students come from poor households (Asadullah et al., 2009), and the majority of madrasa enrollment—both at the primary and the secondary level—is at Alia madrasas (Asadullah and Chaudhury, 2016). While Qawmi madrasas are always cheaper than Alia madrasas, nongovernmental-run or government non-religious schools are even less expensive options for primary education. At the secondary-level, however, madrasas are cheaper than non-religious schools. The share of madrasa enrollment is consistently higher at the secondary-level (22%) than at the primary-level (14%), suggesting either that the dropout rate at the secondary level is higher at nonreligious schools or that households switch schools for their children to madrasas after primary education. Moreover, 12% of primary and 49% of secondary institutes are madrasas (Asadullah and Chaudhury, 2016). Though a lack of supply of secular public schooling may have caused the spread of madrasas, there is no evidence to suggest that madrasas are currently more concentrated in regions where secular public-provisioned schools are in low supply. There is a positive correlation between the number of Alia madrasas and the number of nonreligious public schools (Asadullah et al., 2009).

Madrasa students face at least two structural issues that adversely affect their labor market potential and put them in a disadvantageous position compared to their peers in non-madrasa schools. First, the madrasa curriculum limits a student's opportunity to advance to university education. The Alia madrasa curriculum did not meet the prerequisites for admission in many secular disciplines at the university level until 2013 (Farhin, 2017). The Qawmi madrasa curriculum does not allow its students to sit for many accredited university admission tests.

Second, the quality of the learning outcomes of madrasa students inhibits their university admission and labor market opportunities. Madrasa education has a negative correlation with labor market outcomes such as wage-earning (Asadullah and Chaudhury, 2010). Though students can learn secular subjects at Alia madrasas, the learning outcomes of these students are worse than those of their counterparts at secular schools (Asadullah et al., 2009). The majority of Qawmi madrasas do not offer math at the secondary-level, only three-fifths of Qawmi madrasas offer Bengali—the national language—and about 80% of the secular subject teachers are untrained. Lack of prerequisites and preparedness deprive madrasa students of the opportunity of studying more lucrative disciplines in higher studies and, consequently, they have poorer expected labor market outcomes. A large portion of graduates from Qawmi madrasas takes the low-paying jobs of *imams* or *maulavis* in mosques and madrasas (Asadullah et al., 2019).

Madrasa schooling is negatively associated with positive attitudes towards income-earning women, lower and fixed desired fertility, and higher education for female children (Asadullah and Chaudhury, 2010). Such perceptions may not necessarily help countries such as Bangladesh fight poverty, increase female empowerment, or even curtail the threat of religious extremism.

The labor market and societal implications of madrasa education suggest that a systematic increase in madrasa schooling might have adverse welfare consequences. Given the trend of external migration and madrasa education in Bangladesh, it is important to understand whether, through social remittances, external migration increases madrasa education and has an unintended consequence of reduced labor productivity at home, which in turn may reduce the returns to migration.

3 Data and Descriptive Statistics

I use the 2010 round of the Bangladesh HIES dataset for my primary analysis. The HIES is a nationally representative survey of the population of Bangladesh that is conducted by the Bangladesh Bureau of Statistics every five years. To test whether my findings persist over time, I use the 2016 round of the HIES and estimate the same set of equations.

In total, 55,580 individuals from 12,240 households were interviewed for the HIES 2010, while the HIES 2016 surveyed 168,089 individuals from 46,075 households. Both of these rounds used a two-stage stratified random sampling strategy to select PSUs from the list of the population census enumeration areas. Twenty households were selected for interviews from each of PSU, and all members of a household were interviewed.[4]

As the primary outcome of interest in this paper is the likelihood of a child going to a

[4]See Bangladesh Bureau of Statistics (2011) and Ahmed et al. (2017) for a detailed description of the sampling strategies of the HIES 2010 and the HIES 2016, respectively.

madrasa for schooling, I restrict my analysis to children aged 5 to 18 years. I also focus on the likelihood of a household sending at least one child to a madrasa in order to understand the household-level effect. I also undertake a household-level analysis. I consider a household to be a madrasa-sending household if it has sent at least one child (aged 5 to 18 years) to a madrasa. For the household-level analysis, I restrict my sample to households that at least have one child. The application of these restrictions reduces my sample to 9,178 households and 18,063 children. There were 56,439 children in 32,204 households in the HIES 2016.

The key independent variable of interest here is whether the household has a migrant in a Muslim-majority country. In the migration module of the HIES, each household is asked the following question: "Has any member of your household migrated, either within the country or abroad, during the last 5 years?" If a household has sent at least one member to a Muslim-majority country in the previous five years, I consider that household to have a migration in a Muslim-majority country. I refer to these households as M^1 households. The Muslim-majority countries are Brunei, Iran, Iraq, Jordan, Kuwait, Libya, Malaysia, Oman, Qatar, Saudi Arabia, Turkey, and the United Arab Emirates. I use membership in the Organisation of Islamic Cooperation and having a majority Muslim population as criteria for a country being Muslim-majority one (Organisation of Islamic Cooperation, 2019). Similarly, I consider a household to have a migrant in a Muslim-minority country if that household has sent a migrant to a Muslim-minority country and refer to that as M^2 households. The Muslim-minority countries that households have sent migrant to are Australia, Canada, Germany, Italy, Japan, Mauritius, Russia, Singapore, South Africa, South Korea, Sweden, the United Kingdom, and the United States of America.

There are three key features to this approach of measuring migration that constrain what I am able to identify causally. First, the HIES questionnaire does not include information on exactly when the migration occurred. I can only take an extensive measurement of migration. I cannot measure the length of the period that the migrant has been away from home. Second, it does not include the frequency of that member's migration. As a result, I cannot know if the reported incidence of migration was the first time that individual had migrated or whether that person had migrated before too. Third, though the questionnaire asks whether any currently residing household member returned after migrating, it does not include information on when the migrant has returned. Neither does it collect information about the destination or length of the migration of that returning member. This prevents me from analyzing the effect of return migration. These limitations allow me to identify only the total effect of the first time, repeat, or return migration.

Table 1 reports the descriptive statistics for the outcome variables. There are 1,582 children from 759 M^1 households and 357 children from 178 M^2 households. About 5% of the children from M^1 households attended madrasas, compared to 4% of children from non-M^1 households. In addition, M^1 households are more likely to send at least one of their children to a madrasa than are non-M^1 households. Eight percent of M^1 households send at least one child to a madrasa, while 6% of households without a migrant in a Muslim-majority country send a child to a madrasa. There is no difference between the likelihood of a child from an M^2 household going to a madrasa (4%) and the likelihood of a child from a non-M^2household going to a madrasa (4%). The likelihood of an M^2 household sending at least one child to a madrasa (5%) is slightly lower than that of a non-M^2 household doing so (6%).

Table 2 reports the descriptive statistics for several individual and household label variables. In the estimation, sample there are more male children (52%) and the average age of the children is 11.26 years. About two-thirds of the households live in rural areas (64%). The majority of the households are headed by a Muslim (88%), a male (87%). More than half of the household heads do not have any formal education (52%). Very few households have an adult over 23 years of age who went to a madras (2%). This alludes to the fact that the increase in madrasa education is a recent phenomenon, correlated with the rise in the general enrollment in Bangladesh. Roughly 1% of the households have a member who had returned from abroad in the previous five years.

4 Empirical Strategy

4.1 Estimation Method

Let i indicate individual, h denote household, p refer to PSU, and s indicate sub-district. Then the key equation of interest is:

$$Y_{ihps} = \alpha_s + \alpha_1 M^1_{hps} + \alpha_2 M^2_{hps} + \alpha_3 X_{ihps} + \alpha_4 H_{hps} + \xi_{ihps} \tag{1}$$

In equation 1, $Y_{ihps} = 1$ if individual i of household h in PSU p of sub-district s goes to a madrasa, and 0 if individual i goes to a non-madrasa school. M^1_{hps} is an indicator variable of whether household h in PSU p of sub-district s has a member in a Muslim-majority country where $M^1_{hps} \in \{0, 1\}$. Similarly, M^2_{hps} is an indicator variable of whether household h in PSU p of sub-district s has a member in a Muslim-minority country where $M^2_{hps} \in \{0, 1\}$. X_{ihps} denotes individual-level control variables, and H_{hps} refers to household-level control variables. ξ_{ihps} denotes error terms. α_s represents sub-district-level fixed effects. α_1 and α_2 are the key parameters of interest.

In order to examine whether the individual-level effects reflect a change of household preference at the extensive margin, I also perform a household-level analysis. The outcome variable for the household-level analysis is constructed as follows: $Y_{hps} = 1$ if household h in PSU p of sub-district s sends at least one child to a madrasa, and 0 otherwise. Hence, the equation of interest for the household-level analysis becomes:

$$Y_{hps} = \theta_s + \theta_1 M^1_{hps} + \theta_2 M^2_{hps} + \theta_3 H_{hps} + \zeta_{hps} \tag{2}$$

A major concern in equation 1 is that international migration is not a random phenomenon, that is, $cov(M^j_{hps}, \xi_{ihps}) \neq 0$ where $j \in \{1, 2\}$. Similar concern would be true for equation 2, that is, $cov(M^j_{hps}, \zeta_{hps}) \neq 0$ where $j \in \{1, 2\}$. The household-level decision of sending a migrant abroad may depend on a number of confounding observable and unobservable factors. For example, a household's decision to migrate to a Muslim-majority country might be influenced by that household's preference to send a child to a madrasa; thus, creating a reverse causality problem.

Moreover, a household's decision to send a migrant abroad may depend on the wealth of that household. The wealth of a household can have a simultaneous relationship with the school that a child of that household attends. An income effect can influence the attainment of education. With an increase in income, households decide to send their children to school (that is, the extensive margin of schooling) or to send their children to more expensive schools if the household has the prior belief that more expensive schools are of better quality than cheaper schools. On the other hand, the returns to education of a child will affect household income and wealth. Therefore, wealth is endogenous and needs to be omitted from the equation of interest. This introduces selection bias into the estimation strategy. In addition to wealth, the level of education of the migrant, intra-household power dynamics, and so forth can act as confounding factors for migration and school choice. Simple ordinary least squares will, therefore, produce biased estimates.

To overcome the endogeneity of migration and schooling, I use the instrumental variable method. I use the leave-one-out fraction of migrant households in a PSU as the IV. For household h, a leave-one-out fraction of migrant households in PSU p is calculated by dividing the sum of the total number of migrant households in that PSU except household h by the total number of households in that PSU except for household h. As there are two endogenous variables here, I need to use two IVs. The instrumental variable for each type of migrant household is a leave-one-out fraction of that type of migrant household in the PSU. Formally, for household h in PSU p of sub-district s:

$$Z^j_{p_{(h)}s} = \frac{\sum_{k,k\neq h}^{N} M^j_{kps}}{N-1} \quad \forall j \in \{1,2\}$$

Here, the subscript $p(h)$ refers to the PSU-level average without household h.

The fraction of migrant households in a PSU represents the transnational network of external migrants in the neighborhood. Such a network of external migrants from the neighborhood can help potential migrants in the source country to migrate (Lokshin and Glinskaya, 2009; Munshi, 2003). A network of migrants increases access to information and can reduce uncertainty regarding migration. Therefore, the existence of such a network would facilitate external migration.

I exploit the within sub-district variation of the leave-one-out fraction of migrant households among the neighbors (in this case, PSUs) to identify the causal effect of migration on sending a child to madrasa. Table A1 in Appendix A reports the descriptive statistics of the instrumental variables. Note that within each PSU, there are only two values for each of the instruments. Hence, most of the variation in the instrumental variables come from between PSU variation.

In this instrumental variable framework, there are two first-stage regressions:

$$M^1_{hps} = \lambda_s + \lambda_1 Z^1_{p_{(h)}s} + \lambda_2 Z^2_{p_{(h)}s} + \lambda_3 X_{ihps} + \lambda_4 H_{hps} + \eta_{ihps} \tag{3}$$

$$M^2_{hps} = \gamma_s + \gamma_1 Z^1_{p_{(h)}s} + \gamma_2 Z^2_{p_{(h)}s} + \gamma_3 X_{ihps} + \gamma_4 H_{hps} + \psi_{ihps} \tag{4}$$

The second stage is:

$$Y_{ihps} = \beta_s + \beta_1 \widehat{M^1}_{hps} + \beta_2 \widehat{M^2}_{hps} + \beta_3 X_{ihps} + \beta_4 H_{hps} + \epsilon_{ihps} \tag{5}$$

Here, $\widehat{M^1}_{hps}$ and $\widehat{M^2}_{hps}$ are the predicted values from the first-stage estimation. Thus, β_1 and β_2 are consistent estimators of interest.

β_1 and β_2 are local average treatment effects—the treatment effect of the compliers (Imbens and Angrist, 1994). That is, I identify the treatment effect of the households that would not otherwise send migrants abroad but do so when the fraction of migrant households in the neighborhood increases.

In this individual-level estimation, I include the following control variables: age in years and age squared, whether any adult above 23 years of age went to madrasa, whether the household head is a Muslim, whether the household has any member who was abroad for more than six months during the last five years, the education of the household head, and subdistrict-level fixed effects. I include all but the individual-level controls (age of the individual and age squared) as control variables for the household-level analysis. The first- and second-stage equations for the household-level estimates are presented in Appendix B.

4.2 Identification

I exploit the variation in concentration of migrant households across PSUs within the same sub-district to isolate exogenous variation in a household's decision to send a migrant abroad with respect to the outcome variable—the choice of school for a child of that household. The underlying assumption is that while within sub-district variation in the concentration of migrant households across PSUs is a strong predictor of the likelihood of household h being a migrant household, it does not directly affect the household's schooling decision for a child. Formally, my identification relies on the following assumptions:

$$\lambda_1 \neq 0 \tag{A1.1}$$

$$\gamma_2 \neq 0 \tag{A1.2}$$

$$Cov(Z^1_{p(h)s}, \eta_{ihps}) = 0 \tag{A2.1}$$

$$Cov(Z^2_{p(h)s}, \psi_{ihps}) = 0 \tag{A2.2}$$

Having many migrant households in a neighborhood establishes a network for aspirant migrant households. A network of migrant households would make information more available and accessible. As information is a key constraint for international migration (Beam, 2016; McKenzie et al., 2013), access to information should increase the probability of migration from the neighborhood.

Consequently, the likelihood of a household sending a migrant to a Muslim-majority country should increase in $Z^1_{p(h)s}$. This hypothesis is tested by obtaining a statistically significant $\hat{\lambda_1}$ from equation 3. Similarly, whether the likelihood of migration to a Muslim-minority country is increasing in $Z^2_{p(h)s}$ can be tested by obtaining a significant $\hat{\gamma_2}$ from equation 4.

Table 3 reports the results of the estimation of the first stage. The strong and statistically significant estimates of the instruments for both Muslim-majority and Muslim-minority households imply that the instrumental variables satisfy the relevance condition, that is, assumptions A1.1 and A1.2. Using the weak instrument test of Olea and Pflueger (2013), I find that the Olea-Pflueger F-statistics for Z^1 and Z^2 are much higher than the critical values for 5% and 10% of the worst-case bias from a weak instrument, respectively. Thus, the instruments are not weak, and the weakness of the instruments does not pose any major threat to the validity of my estimation approach.

One major threat to identification is the violation of assumptions A2.1 and A2.2—that is, the exclusion restriction—as the validity of the causal estimates relies on satisfying these assumptions. It is likely that the concentration of migrants in the neighborhood directly affects a household's likelihood to send at least one child to a madrasa, rendering estimates inconsistent. To tackle this, I exploit the plausibly random within sub-district variation in of concentration of migrants across PSUs. I assume that after controlling for pre-determined household- and individual-level characteristics, within sub-district variation in the concentration of migrant households across PSUs does not correlate with the household's unobservable type. However, unlike the relevance condition, there is no direct statistical method to test this assumption.

To address the concern that the within sub-district variation of migrant across PSUs do not violate the exclusion restriction, I divide the residuals from the second stage into two parts following the strategy of Fruehwirth et al. (2019): an individual-specific component (u_{ips}) and a PSU-specific component ($\nu_{p(i)s}$) that includes PSU-level direct effects on school choice or other PSU-level unobservables. As a result, the error term can be written as $\epsilon_{ips} = u_{ips} + \nu_{p(i)s}$. For the estimates to be consistent, Assumption A2 becomes:

$$Cov(Z^1_{p_{(h)}s}, u_{ihps}) = 0 \tag{A2.1$'$}$$

$$Cov(Z^1_{p_{(h)}s}, \nu_{p(h)s}) = 0 \tag{A2.2$''$}$$

Violation of condition A2.1$'$ can occur if there are unobservables that determine both household-level outcome and migration. While sub-district-level fixed effects control for selection on sub-district-level characteristics, condition A2.1$'$ can still be violated if a household changes its location, and by extension, PSU, based on the fraction of migrants there are. That is, to migrate internationally, a household can make the strategic decision to migrate internally to PSUs with more migrant households. Learning about migration opportunities certainly induces households to make strategic choices (Shrestha, 2017).

However, such strategic movement seems implausible because of the cost of migration. Both internal and international migration are expensive endeavors. Credit constraints restrict the ability of households to send migrants abroad (Mendola, 2008). Internal migration also is often undertaken by households with access to more income (Munshi and Rosenzweig, 2016). In addition, internal migration in Bangladesh is principally constrained by a lack of credit rather than by a lack of information (Bryan et al., 2014). International migration being much more expensive than internal migration, it seems implausible that Bangladeshi households would strategically move to PSUs that would facilitate international migration rather than migrating to urban areas to obtain better-paid jobs. Hence, I do not consider such a violation of condition A2.1′ a likely threat.

Condition A2.2″ can be violated if there are PSU-level variables that correlate with both the outcome variable and the instrumental variables. This is a concern if there are observables or unobservables that vary at the PSU-level and are correlated with the fraction of migrants in the PSU and also affect sending a child to a madrasa. One way to alleviate this concern is to show that the causal estimates do not change when PSU-level leave-one-out average of outcome variables and control variables are included in the main specification. In Section 5.2, I show that the causal estimates do not change when PSU-level observables are controlled for. If the estimates were driven by the PSU-specific factors, then the inclusion of these additional controls would significantly change my results. Thus, I argue that a violation of condition A2.2″ is not highly likely either and, therefore, the validity of my identification is not threatened by the exclusion restrictions not being satisfied.

5 Estimation and Discussion

5.1 Discussion of the Main Results

Estimation of equation 5 shows that a child from a household with a migrant in a Muslim-majority country (M^1) is 8.4 percentage points more likely to go to a madrasa, while if the child is from a household with a migrant in a Muslim-minority country (M^2), then there is no discernible difference in the likelihood of that child being sent to a madrasa. I report the results of this estimation in Panel A of Table 4.

This result is driven by the causal impact of a household sending a member to a Muslim-majority country on the probability of it sending a male child to a madrasa. A male child from an M^1 household is 16 percentage points more likely to be sent to a madrasa, while there is no impact on the likelihood of a female child being sent to a madrasa. As with the estimates for a child of any sex, there is no impact of M^2 households on the likelihood of either a male child or a female child being sent to a madrasa.

The increase in the likelihood of madrasa schooling is due to households switching from non-madrasa schools to madrasas and not because of a general increase in school enrollment. The results presented in Panel B of Table 4 show that there is no effect of migration on schooling (both madrasa and non-madrasa). That is, there is no significant income effect on going to school. This suggests that M^1 households switch from non-madrasa schools to madrasa schools.

Having a migrant in a Muslim-majority country also affects whether the household sends at least one child to a madrasa (9.8 percentage point increase), and, similarly to individual-level effects, this is driven by the increased likelihood of the household sending at least one male child to a madrasa (12.4 percentage point increase). Panel A of Table 5 reports the results for this estimation. Given that the dependent variable here is whether the household sends at least one child to a madrasa, the household-level effects indicate that, in addition to an increase at the intensive margin, migration also causes an increase at the extensive margin. As there is no increase in schooling as a whole, this increase at the extensive margin further suggests that the effect I find is a switching effect. It should be noted that the household-level analysis was conducted only on households with children. The sex-specific household-level results are similarly estimated using only households that have at least one child of that particular sex.

Though households are switching some of their children to madrasas from non-madrasa schools because of migration, they are not doing this for all of their children. The estimates presented in Panel B of Table 5 show that there is no causal impact of either M^1 or M^2 on the likelihood that a household would send at least one child to a non-madrasa school. There is no impact when I look at the likelihood of sending at least one child of any particular sex, either. This suggests that households are switching schools for some, but not all, male children of the household.[5]

These results establish that households that have migrants in Muslim-majority countries switch schools from non-madrasa schools to madrasas for some of their male children but that they do not do it for all their male children. As indicated above, the existing literature suggests that madrasa students have worse learning outcomes than non-madrasa students (Asadullah et al., 2009). There is also a negative relationship between madrasa education and wage income (Asadullah and Chaudhury, 2010). This is also corroborated by the fact that madrasa-educated students cannot apply for good university degrees and, therefore, cannot get good jobs.

To ascertain the relationship between madrasa education and the labor market, I estimate the relationship between madrasa education and labor market outcomes for the working-age population—that is, for all persons aged 15 to 64 years. I explore the relationship between madrasa education and two key outcome variables—labor market participation and current employment. Table A3 in Appendix A reports the results of the estimation. I find that madrasa education has a significant negative relationship with these labor market outcomes of the male working-age population. The likelihood of labor market participation by males decreases by about four percentage points depending on the specification. The employment rate also declines by about four percentage points. The reduction of labor force participation and current employment indicates that, as regards the labor market, madrasa educated males are relatively worse off than the non-madrasa-educated males.

The negative relationship between madrasa education and learning outcomes and labor market outcomes suggests that a systematic increase of madrasa education might adversely influence the human capital development of the society concerned. On the other hand, external migration is considered extremely important due to the financial remittances it provides. Given that the reduction in human capital is unaccounted for, the calculated return of external migration is overestimated, and the actual return is less than what we have so far thought it is.

[5]To observe the joint effect of M^1 or M^2, I re-estimate the equations of interest including an interaction of M^1 and M^2. The results are reported in Table A2 in Appendix A. The interaction terms are not statistically significant for any of the specifications.

A systematic increase in madrasa schooling through international migration implies that with an increase in international migration from Bangladesh, more children will be sent to madrasas. Given the poor quality of learning and the adverse labor market outcomes of madrasa graduates, these children will be in a disadvantageous position in terms of earning potential relative to their peers at non-madrasa schools. This may further exacerbate inequality in the society. Hence, a systematic increase in madrasa education provides an economic justification for policy initiatives to improve the quality of madrasa education.

5.2 Robustness Checks

5.2.1 Validity of identification

To tackle the concern that condition A2.2′′ can be violated, I plug the PSU-level leave-one-out average of outcome and control variables into the main specification and re-estimate the results. The variables I select are whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has a member who returned from abroad, and whether the household head has secondary education or above. I also include, in a separate estimation, the leave-one-out mean of the outcome variable. Then I estimate the equation with both the pre-determined neighbor characteristics and outcomes. Table 6 reports the results of the estimation.

I find that an inclusion of the pre-determined neighbor characteristics does not change the results, though their magnitude becomes slightly larger. When I include the average of the neighbor outcome, again, the magnitude is smaller—but qualitatively, the results remain the same. When I include both the neighbor characteristics and the neighbor outcome, the main results do not change either. As the main results do not change when I add these additional controls, I can rule out the concern of PSU-level confounding variables violating condition A2.2′′ and thereby threatening the validity of the identification strategy. Therefore, I argue that the estimates I find can be considered causal without there being a concern about inconsistency.

I also check whether my results are robust to the relaxation of strict exogeneity conditions following the methodology laid out by Conley et al. (2012). I implement their methodology following the implementation by Nunn and Wantchekon (2011) and Azar et al. (2017). The methodology of Conley et al. is as follows: relax the assumption of instruments being strictly exogenous and assume that the instruments enter the second stage estimation. That is, I relax the assumptions $Cov(Z^1_{p_{(h)}s}, \eta_{ihps}) = 0$ and $Cov(Z^2_{p_{(h)}s}, \psi_{ihps}) = 0$ and assume that Z^1 and Z^2 enter the second stage with coefficients β_{Z^1} and β_{Z^2}, respectively. I compute the bounds of the consistent values of the coefficients of M^1 and M^2 by making assumptions about the values of β_{Z^1} and β_{Z^2}.

I regress the outcome variable on the household-level migration variables, the instrumental variables, and the full set of control variables used in the preferred specification. The coefficients of the instrumental variables from this estimation are taken as upper (lower) bound of the values of β_{Z^1} and β_{Z^2} if the coefficient is positive (negative), while zero is assumed to be lower (upper) bound.

As my primary result is that migration to a Muslim-majority country causes an increase in religiosity in the home-country, I focus on the effects of M^1 for male children when I assume plausible exogeneity of Z^1. The coefficient of Z^1 is 0.127 in the reduced form, where the outcome variable is regressed on all the regressors and the instruments. Hence, I assume that the upper bound of β_{Z^1} is 0.127 and the lower bound is zero.[6] The results of this computation are reported in Table 7. The confidence interval of the coefficient of the primary variable of interest, that is, a household having a migrant in a Muslim-majority country, includes zero under the assumed bound of β_{Z^1}. The maximum value of β_{Z^1} for which the coefficient for the individual-level effect on the schooling of male children does not include zero (I refer to it as $\beta_{Z^1_{max}}$) is 0.029, which is roughly 23% of the upper bound of β_{Z^1}. This means that my main results are robust for a minor violation of the strict exogeneity assumption.

Another potential concern here is the "exclusion bias." This is a mechanical negative bias created by the leave-one-out means (Caeyers and Fafchamps, 2016). For illustration purposes, consider Table B1 in Appendix B. Note that within each PSU, $Z^1_{p_{(h)}s}$ is smaller for households with M^1_{hps}=1 than for households with M^1_{hps}=0. That is, $Z^1_{p_{(h)}s}$ is mechanically negatively correlated with M^1_{ips}. Hence, when M^1_{hps} is regressed on $Z^1_{p_{(h)}s}$, the estimates have

[6] Assuming non-negative values for β_{Z^1} does not threaten my results as, when I assume β_{Z^1} to be negative, the confidence intervals of β_1 do not include zero and are always positive.

a negative bias (Guryan et al., 2009). Due to the exclusion bias, my first stage estimates are potentially downward biased. However, we are interested in the correlation of the first stage, not causation. Hence, I argue that the exclusion bias does not threaten the identification of the second stage.

5.2.2 Intertemporal external validity

To verify whether the results hold over time, I estimate my main results using the HIES 2016. As the HIES is a cross-sectional dataset, the HIES 2016 was collected based on a new sampling. If the results of the HIES 2010 and 2016 were inconsistent, that would raise doubts about the validity of the identification.

I pooled data from the HIES 2010 and the HIES 2016—to estimate whether the results are intertemporally consistent—and estimate equation 5, including a dummy that indicates the survey year and an interaction term of that dummy with all other right-hand side variables. Table 8 reports the results of the pooled estimation. The causal impact of a household sending a migrant to a Muslim-majority country on sending a male child of the household to a madrasa persists in 2016, while additional causal impacts on sending a female child are found. The results from standalone estimations using the HIES 2016 data are presented in Tables A4 and A5 in Appendix A. The effect of migration to a Muslim-majority country on the likelihood of a male child being sent to a madrasa in 2016 is 0.7 percentage points more than that for 2010, and the point estimates become more precise. The likelihood for a female child, on the other hand, increases by 17.5 percentage points between 2010 and 2016.

I find that, over time, the effects on sending male children to madrasas persist and additional effects on sending female children to madrasas appear to manifest— implying that the intensity of the causal impact has increased over time. A general increase in female education can partially explain the increase in madrasa schooling for female children. However, the increase in madrasa schooling for male children is not due to an increase in enrollment. Hence, the estimates from the HIES 2016 are similar to or stronger than those from the HIES 2010.

5.3 Mechanisms

There are three potential mechanisms through which the causal impact would work—an income effect, a learning channel, and social remittances. I show that the income effect and the learning channel mechanisms are implausible and argue that the most plausible mechanism is the social remittances.

An income-effect mechanism would work if a household sends its children to madrasas when the income of the household increases, which would otherwise be difficult due to budgetary constraints. If madrasa schooling is more expensive than the non-madrasa options, an increase in income will allow households to send their children to madrasas. However, we know that madrasas in Bangladesh are not more expensive than non-madrasas, especially public schools. Qawmi madrasas are cheaper than Alia madrasas, and non-madrasa schools might be more expensive considering all the outside tutoring fees that a household might have to pay. An increase in income, therefore, is not likely to increase madrasa schooling. Hence, the income-effect mechanism seems implausible.

The second potential mechanism is the learning channel. After a member has migrated abroad, migrant households are likely to learn more about the Muslim-majority countries and to have more information about what might help a child to migrate in the future. Households might conclude that having a madrasa education might be beneficial for their children to migrate in the future because they learn Arabic. However, this mechanism seems impossible. The number of teachers who can give proper training in spoken Arabic in the Bangladeshi madrasas is very low, and the quality of Arabic learning is also very poor (Antara, 2019; Bhuiyan, 2018). The Arabic learned in the madrasas in Bangladesh is not useful for migrating to Muslim-majority countries—information that the migrant household would have through the learning channel.

It is also possible that households learn how religious schooling might help their children to migrate in the future. That is, madrasa education works as a signaling device. As a result, more migrant households send their children to madrasas. This does not seem to be plausible either as there is no evidence that the religion of migrants determines their employability or wage payment in Muslim-majority countries. A significant portion of the migrants in the

Persian Gulf come from countries where Islam is not the dominant religion (e.g., India, the Philippines, and Sri Lanka). Migrants from these countries are also high on the list of top remittances senders from the Gulf countries (Naufal, 2011; World Bank, 2019).

As I rule out an income effect or the learning channel, the most plausible mechanism is social remittances. The significant influence of migration to a Muslim-majority country on increased enrollment in madrasa education must concern the unique aspect that the madrasa offers—religious schooling. Given that madrasa education is primarily focused on the teaching of religion and that the causal effect I find is for households that have sent a migrant to a Muslim-majority country, this indicates that increased religiosity due to social remittances from the destination country is driving increased madrasa enrollment for children from migrant households. The absence of a causal impact of migrating to a Muslim-minority country further strengthens this argument.

Given that madrassa education is negatively associated with labor market outcomes, a social remittance mechanism would make economic sense if there are heterogeneous treatment effects by household income. The rationale is that a relatively more affluent household would have lower constraints to giving up future income potential if it decides to send a child to a madrasa. I test this implication of the social remittance mechanism by estimating treatment effect heterogeneity by income in Table 9. I split the households into two groups based on their income—above- and below-median income households. I find that only households with above-median income manifest a causal impact of having a migrant in a Muslim-majority country on the likelihood of sending a male child to a madrasa (31.6 percentage points increase). That relatively wealthier households are able to forgo future income potential by sending a male child to a madrasa provides strong evidence that the increase in madrasa schooling works through the social remittance mechanism.

Another implication of the social remittance mechanism is that the increase in madrasa schooling should manifest in households whose heads are Muslims. I test this by estimating the main results after splitting the sample by the religion of the household head. The results are reported in Table 10. Only Muslim households that have a migrant in a Muslim-majority country are more likely to send male children to madrasas, which indicates the consistency of the social remittance mechanism.

The social remittance mechanism is consistent with the existing findings in the sociology literature. Migration makes a person undergo a transformation of his or her identity. External migrants are likely to become more religious (Simpson, 2003; Williams et al., 2014). Muslim labor migrants from South Asia experience an enhanced sense of religiosity and orthodoxy after the migration (see Kibria, 2008). Migrants are exposed to the pain of dislocation, and they might revert to their religious identity as a coping mechanism. In addition, having migrated to a Muslim-majority country, especially one in the Persian Gulf, where the influence of religion on norms, cultures, and institutions is more overt, a religious Muslim person would potentially want to adhere to norms that would reflect the lifestyle of an authentic Muslim. The migrants can transmit this enhanced sense of religious identity and religiosity to the household in the home country. The households would be inclined to imitate norms and behavior that reflect increased adherence to religious practices. Through such practices, they can also gain a higher social status in a society that values religiosity (Kibria, 2008).

Given that the plausible mechanism is a transfer of social remittances, the following channel is at work: a household sends a migrant to a Muslim-majority country, the migrant transmits financial and social remittances back to the household in the home country, the social remittances change the household's religiosity and preference, and then the household changes the schooling of a male child from a non-madrasa school to a madrasa.

An important factor in the increase of religiosity through migration is the context. In this context, both the home and host countries are Muslim-majority countries, religion has a significant presence in the social and political norms of the host country, and religious identity has a significant place in the lives of the people of the home country. The results might differ in other contexts. For instance, it is unlikely that the Filipino migrants in the Persian Gulf are causing religious conversion from Christianity to Islam in the Philippines. Similarly, even if the dominant religion of the host country and the home country are the same (for instance, migration of Mexicans to the United States), migration might not influence an increase in the religiosity of the home country because of the relative difference in the influence of religion in the social and political norms of the two countries. In addition, migration from Bangladesh to the United States/United Kingdom might influence a transfer of secular practices to the social lives of the people in the home country. Thus, an extension of my findings to a different setting will depend on the context, limiting the external validity of this paper.

6 Conclusion

I have investigated whether international migration increases religiosity in the home country through social remittances. My findings relate to the small but growing literature that examines migration-induced social remittances in the home country. I have found that there is a strong migration-induced transfer of norms from Muslim-majority countries to Bangladesh that increases religiosity, as manifested by the strong and sizable positive causal effect on the likelihood of sending a male child to a madrasa. With the passage of time, households also start sending their female children to madrasas. I have found that the increase in madrasa education is a result of changing schools for those children who are already attending schools, rather than due to a general increase in schooling. I have also found that though households switch schools for some of the male children, they do not switch schools for all the children. That is, there is no change in the likelihood of the household continuing to send at least one child to a non-madrasa school.

I could not measure religiosity directly due to data limitations and have had to rely on the incidence of madrasa schooling to indicate religiosity. Such an indirect measure, however, does not pose a major threat to my conclusion. I ruled out an income effect and learning about migration as potential mechanisms for the causal estimate and have shown that international migration can cause an increase in madrasa schooling only through a rise in religiosity.

My findings suggest that there is a systematic increase in madrasa education due to the increasing external migration from Bangladesh to Muslim-majority countries. Madrasa graduates have low learning outcomes and poor labor market outcomes. A systematic increase in madrasa education, therefore, would lead to adverse human capital production in the society concerned. Hence, increased madrasa education would lead to a reduction in the returns to external migration. This suggests that we should pay attention to improving the quality of madrasa education so that the learning and labor market outcomes of madrasa graduates can improve.

Madrasas have a strong presence in the Bangladeshi society. The findings of this paper suggest that the same household often sends its children to different types of schools. This clearly demonstrates that there is a demand for madrasa schools, and, thus, it is important to consider how to improve the learning outcomes of madrasa students so that they can compete in the labor market with their peers from non-madrasa schools.

One key limitation of this paper is that the instrument used is an unconventional one. However, I demonstrated that the results are robust to the potential violations of the identification assumption and, therefore, that this limitation does not threaten my key findings. In addition, as I used instrumental variables, I could only estimate the local average treatment effects. Estimating an average treatment effect is recommended for a possible future research agenda.

My findings are also context dependent. A similar increase of religiosity in the home country may or may not be observed in a context in which the religion of the host and home countries are different or in which the relative influence of religion in the collective lives of people in the host and home countries are dissimilar. However, international migration is very important to developing economies, and we need to understand anything that may influence the returns to migration—more so when the direction of change in the returns to migration is negative. Thus, it is essential to undertake further research to understand whether a transfer of norms in a different context that may also reduce the returns to migration occurs.

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Tables

Table 1: Descriptive Statistics of Individual- and Household-Level Outcome Variables

	Household has a migrant in a Muslim-majority country		Household has a migrant in a Muslim-minority country		All households
	No	Yes	No	Yes	
Individual-level					
Goes to madrasa					
A child	0.04	0.05	0.04	0.04	0.04
A male child	0.04	0.05	0.04	0.04	0.04
A female child	0.04	0.04	0.04	0.03	0.04
Goes to non-madrasa school					
A child	0.56	0.61	0.56	0.63	0.56
A male child	0.54	0.61	0.55	0.62	0.55
A female child	0.58	0.61	0.58	0.65	0.58
Total number of children	16,481	1,582	17,706	357	18,063
Household-level					
Goes to madrasa					
At least one child	0.06	0.08	0.06	0.05	0.06
At least one male child	0.04	0.04	0.04	0.04	0.04
At least one female child	0.03	0.04	0.03	0.03	0.03
Goes to non-madrasa school					
At least one child	0.69	0.77	0.70	0.74	0.70
At least one male child	0.44	0.51	0.44	0.46	0.44
At least one female child	0.43	0.48	0.44	0.49	0.44
Total number of households	8,419	759	9,000	178	9,178

Table showing the means of the individual- and household-level outcome variables by each type of migrant household and for the total sample. The omitted categories of the outcome variables are—not going to any school at the individual-level and not sending any child to school at the household-level. The individual-level sample is restricted to children of ages 5 to 18 years, and the household-level sample is restricted to households who have at least one child.

Table 2: Descriptive Statistics of Other Individual- and Household-Level Variables

	Household has a migrant in a Muslim-majority country		Household has a migrant in a Muslim-minority country		All households
	No	Yes	No	Yes	
Individual-level					
Sex of the child (male=1)	0.52	0.51	0.52	0.47	0.52
Average age (in years)					
All children	11.23	11.53	11.24	11.94	11.26
All male children	11.30	11.44	11.31	11.73	11.32
All female children	11.15	11.62	11.17	12.13	11.20
Total number of children	16,481	1,582	17,706	357	18,063
Household-level					
Household head is					
Male	0.91	0.46	0.88	0.58	0.87
Muslim	0.88	0.96	0.88	0.94	0.88
Household location					
Metropolitan	0.09	0.06	0.09	0.02	0.09
Urban	0.27	0.24	0.27	0.31	0.27
Rural	0.64	0.70	0.64	0.67	0.64
Household has					
An adult (>23 years old) who went to a madrasa	0.02	0.02	0.02	0.03	0.02
A member who returned from abroad in the previous five years	0.01	0.04	0.01	0.04	0.01
Education of household head					
No formal education	0.52	0.47	0.52	0.39	0.52
Below primary	0.06	0.05	0.06	0.04	0.06
Primary	0.10	0.14	0.10	0.12	0.10
Junior secondary	0.09	0.13	0.10	0.13	0.10
Secondary	0.13	0.17	0.13	0.21	0.13
Higher secondary	0.04	0.02	0.04	0.06	0.04
Technical post secondary	0.06	0.02	0.06	0.04	0.06
Total number of households	8,419	759	9,000	178	9,178

Table showing the means of the individual- and household-level characteristics by each type of migrant household and for the total sample. The individual-level sample is restricted to children of ages 5 to 18 years, and the household-level sample is restricted to households who have at least one child.

Table 3: First-Stage Estimates

	Dependent variable: Household has a migrant in a Muslim-majority country			**Dependent variable: Household has a migrant in a Muslim-minority country**		
	Second-stage estimation sample universe:					
	Individual		Household	Individual		Household
	(1) Male children	(2) Female children	(3) All households	(4) Male children	(5) Female children	(6) All households
The PSU-level leave-on-out fraction of households with a migrant in a						
Muslim-majority country	0.679***	0.628***	0.683***	0.050***	0.054***	0.054***
	(0.045)	(0.043)	(0.036)	(0.017)	(0.019)	(0.014)
Muslim-minority country	0.204***	0.056	0.196***	0.319***	0.528***	0.407***
	(0.072)	(0.087)	(0.062)	(0.081)	(0.121)	(0.093)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr.	0.12	0.11	0.12	0.04	0.06	0.04
Olea-Pflueger F-statistics	189.36	145.75	292.25	18.25	21.09	21.91
Critical value for 5% of worst-case bias	19.54	15.21	18.79	26.04	29.60	29.35
Critical value for 10% of worst-case bias	12.63	10.06	12.18	16.44	18.52	18.38
N	9,322	8,741	9,178	9,322	8,741	9,178

All regressions include the following control variables: whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Columns 1, 2, 4, and 5 also include the age of the child and its square. Columns 3 and 6 are restricted to households that have at least one child. F-statistics is for the test that the coefficient of excluded instrumental variable(s) is equal to zero. The critical values of the worst case bias are obtained from the weak instrument test of Olea and Pflueger (2013). Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Individual-Level Effects of a Household Having a Migrant Abroad on the Schooling Decision of a Child

Panel A
Dependent variable: Goes to a madrasa

	A child		A male child		A female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	-0.002	0.084*	-0.003	0.160**	0.001	-0.010
	(0.011)	(0.051)	(0.015)	(0.063)	(0.012)	(0.060)
Muslim-minority country	-0.013	-0.061	-0.021	-0.229	-0.006	0.078
	(0.019)	(0.162)	(0.024)	(0.212)	(0.022)	(0.214)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.06	0.06	0.07	0.07	0.06	0.06
N	10,889	10,889	5,473	5,473	5,416	5,416

Panel B
Dependent variable: Goes to school

	A child		A male child		A female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	0.037***	0.023	0.073***	-0.023	-0.005	0.058
	(0.012)	(0.079)	(0.015)	(0.089)	(0.016)	(0.096)
Muslim-minority country	0.020	-0.051	0.058*	0.127	-0.019	-0.181
	(0.028)	(0.302)	(0.034)	(0.404)	(0.038)	(0.313)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.60	0.60	0.59	0.59	0.62	0.62
N	18,063	18,063	9,322	9,322	8,741	8,741

All regressions include the following control variables: age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Household-Level Effects of a Household Having a Migrant Abroad on the Schooling Decision of Its Children

Panel A

Dependent variable: Household sends to a madrasa

	At least one child		At least one male child		At least one female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	0.010	0.098**	0.001	0.124**	0.006	0.027
	(0.011)	(0.048)	(0.012)	(0.056)	(0.010)	(0.048)
Muslim-minority country	-0.015	0.045	-0.003	-0.115	-0.004	0.045
	(0.016)	(0.162)	(0.021)	(0.204)	(0.018)	(0.152)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.06	0.06	0.05	0.05	0.04	0.04
N	9,178	9,178	6,492	6,492	6,183	6,183

Panel B

Dependent variable: Household sends to a non-madrasa school

	At least one child		At least one male child		At least one female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	0.068***	0.115	0.084***	-0.138	0.035	0.199
	(0.016)	(0.090)	(0.023)	(0.109)	(0.021)	(0.123)
Muslim-minority country	0.018	-0.082	0.057	0.804	0.016	-0.268
	(0.033)	(0.402)	(0.044)	(0.538)	(0.044)	(0.368)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.70	0.70	0.63	0.63	0.65	0.65
N	9,178	9,178	6,492	6,492	6,183	6,183

All regressions include the following control variables: if the household has an adult above 23 years of age who went to madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Columns 1 and 2 are restricted to households that have at least one child of any sex. Columns 4-6 are restricted to households who have at least one child of the sex that the dependent variable is referencing to. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Tests on PSU-Level Confounding Variables Influencing Madrasa Schooling

Panel A
Dependent variable: A male child goes to a madrasa

	Baseline results	Neighbor household characteristics as controls	Neighbor household outcomes as controls	Neighbor household outcomes and characteristics as controls
	(1)	(2)	(3)	(4)
Household has a migrant in a				
Muslim-majority country	0.160**	0.164**	0.123**	0.132**
	(0.063)	(0.070)	(0.056)	(0.063)
Muslim-minority country	-0.229	-0.247	-0.226	-0.231
	(0.212)	(0.213)	(0.179)	(0.187)
Sub-district fixed effect	Yes	Yes	Yes	Yes
N	5,473	5,473	5,473	5,473

Panel B
Dependent variable: A female child goes to a madrasa

	Baseline results	Neighbor household characteristics as controls	Neighbor household outcomes as controls	Neighbor household outcomes and characteristics as controls
	(1)	(2)	(3)	(4)
Household has a migrant in a				
Muslim-majority country	-0.010	-0.047	-0.028	-0.053
	(0.060)	(0.064)	(0.045)	(0.053)
Muslim-minority country	0.078	-0.004	0.090	0.031
	(0.214)	(0.197)	(0.168)	(0.169)
Sub-district fixed effect	Yes	Yes	Yes	Yes
N	5,416	5,416	5,416	5,416

All coefficients are 2SLS estimates. All regressions include the following control variables: age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. In addition, column 2 includes the PSU-level leave-one-out average of the following variables- if the household has an adult above 23 years of age who went to madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and if the household head has above secondary-level education. Column 3 includes the PSU-level leave-one-out average of the outcome variable. Column 4 includes all the controls of columns 2 and 3. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Plausible Exogeneity of the Instruments

Panel A: Madrasa schooling of male children	A male child goes to a madrasa	Household sends at least one male child to a madrasa
	(1)	(2)
	2SLS	2SLS
The PSU-level leave-on-out fraction of households with a migrant in a		
Muslim-majority country	0.127***	0.090***
	(0.033)	(0.027)
Muslim-minority country	-0.054	-0.012
	(0.078)	(0.065)
Bounds of the coefficient for the household having a migrant in a Muslim-majority country		
Lower bound	-0.140	-0.119
Upper bound	0.282	0.232
$\beta_{Z^1_{max}}$	.025	0.009
Sub-district fixed effect	Yes	Yes
N	5,473	6,492

Panel B: Madrasa schooling of female children	A female child goes to a madrasa	Household sends at least one female child to a madrasa
	(1)	(2)
	2SLS	2SLS
The PSU level leave-on-out fraction of households with a migrant in a		
Muslim-majority country	0.002	0.021
	(0.030)	(0.025)
Muslim-minority country	.040	0.026
	(0.076)	(0.063)
Bounds of the coefficient for the household having a migrant in a Muslim-majority country		
Lower bound	-0.130	-0.100
Upper bound	0.114	0.127
$\beta_{Z^1_{max}}$	N/A	N/A
Sub-district fixed-effect	Yes	Yes
N	5,416	6,183

Following Conley et al. (2012), I assume that the instrumental variables enter the reduced form equation with coefficients β^1_Z and β^2_Z. The bounds of the coefficient for migration variables are computed at a 95% significance level after assuming β^1_Z and β^2_Z are bounded between zero and their estimated values reported in the table. $\beta_{Z^1_{max}}$ refers to the maximum value of β^1_Z for which the confidence intervals for second stage estimates of the migration variables will exclude zero. All regressions include the following control variables: age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Column 2 for each panel is restricted to households that have at least one child of the sex that the dependent variable is referring to. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Individual-level Effects from Pooling the 2010 and 2016 Rounds of the Bangladesh Household Income and Expenditure Survey

Dependent variable: Goes to a madrasa			
	A Child	A male child	A female child
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
Household has a migrant in a			
Muslim-majority country*Survey year=2016	0.096	0.014	0.181***
	(0.060)	(0.076)	(0.068)
Muslim-minority country*Survey year=2016	0.111	0.306	-0.011
	(0.212)	(0.277)	(0.226)
Household has a migrant in a			
Muslim-majority country	0.076*	0.155***	-0.007
	(0.045)	(0.058)	(0.055)
Muslim-minority country	-0.046	-0.229	0.072
	(0.131)	(0.182)	(0.165)
Survey year=2016	0.168	0.099	0.220
	(0.146)	(0.180)	(0.160)
Sub-district fixed effect	Yes	Yes	Yes
N	60,677	31,000	29,677

All regressions include the following control variables: age of the child and square of age, if any adult above 23 years of age went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, the education of the household head, and all these variables interacted with survey year dummy. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Heterogeneous Effects on Madrasa Schooling by Household Income

Panel A: Madrasa schooling of male children

	A male child goes to a madrasa		Household sends at least one male child to a madrasa	
	(1)	(2)	(3)	(4)
	Below median income	Above median income	Below median income	Above median income
Household has a migrant in a				
Muslim-majority country	0.104	0.316**	0.069	0.219**
	(0.085)	(0.148)	(0.066)	(0.098)
Muslim-minority country	0.110	-1.562	0.048	-0.393
	(0.192)	(1.269)	(0.186)	(0.596)
Sub-district fixed effect	Yes	Yes	Yes	Yes
Sample mean	0.06	0.07	0.05	0.06
N	2,538	2,933	3,062	3,429

Panel B: Madrasa schooling of female children

	A female child goes to a madrasa		Household sends at least one female child to a madrasa	
	(1)	(2)	(3)	(4)
	Below-median income	Above-median income	Below-median income	Above-median income
Household has a migrant in a				
Muslim-majority country	-0.068	0.083	0.003	0.096
	(0.081)	(0.113)	(0.055)	(0.101)
Muslim-minority country	0.092	0.107	0.093	0.005
	(0.297)	(0.549)	(0.180)	(0.436)
Sub-district fixed effect	Yes	Yes	Yes	Yes
Sample mean	0.05	0.06	0.04	0.05
N	2,534	2,882	2,947	3,234

All coefficients are 2SLS estimates. All regressions include the following control variables: whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Columns 1 and 2 also include age and square of age. Columns 3 and 4 of each panel are restricted to households that have at least one child of the sex that the dependent variable is referring to. Columns 1 and 3 are estimates for households with below-median total income. Columns 2 and 4 are estimates for households with above-median total income. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Heterogeneous Effects on Madrasa Schooling by the Religion of the Household Head

Panel A: Madrasa schooling of male children

	A male child goes to a madrasa		Household sends at least one male child to a madrasa	
	(1)	(2)	(3)	(4)
	Household head Muslim	Household head non-Muslim	Household head Muslim	Household head non-Muslim
Household has a migrant in a				
Muslim-majority country	0.178***	0.337	0.135**	0.158
	(0.068)	(1.442)	(0.061)	(0.440)
Muslim-minority country	-0.213	-2.885	-0.090	-2.832
	(0.224)	(14.593)	(0.215)	(12.273)
Sub-district fixed effect	Yes	Yes	Yes	Yes
Sample mean	0.08	0.00	0.06	0.00
N	4,860	608	5,761	725

Panel B: Madrasa schooling of female children

	A female child goes to a madrasa		Household sends at least one female child to a madrasa	
	(1)	(2)	(3)	(4)
	Household head Muslim	Household head non-Muslim	Household head Muslim	Household head non-Muslim
Household has a migrant in a				
Muslim-majority country	-0.005	0.116	0.034	0.043
	(0.065)	(0.187)	(0.052)	(0.082)
Muslim-minority country	0.045	-0.907	0.025	-0.409
	(0.216)	(1.256)	(0.155)	(0.508)
Sub-district fixed effect	Yes	Yes	Yes	Yes
Sample mean	0.07	0.00	0.05	0.00
N	4,808	601	5,472	703

All coefficients are 2SLS estimates. All the regressions include the following control variables: whether the household has an adult aged 23 years or older who went to a madrasa, whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Columns 1 and 2 also include age and square of age. Columns 3 and 4 of each panel are restricted to households that have at least one child of the sex that the dependent variable is referring to. Columns 1 and 3 are estimates for households whose head is a Muslim. Columns 2 and 4 are estimates for households whose head is a non-Muslim. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A

Table A1: Descriptive Statistics of the Instrumental Variable

	Household has a migrant in a Muslim-majority country		Household has a migrant in a Muslim-minority country	
	No	Yes	No	Yes
The PSU-level leave-on-out fraction of households with a migrant in a				
Muslim-majority country	0.07	0.21	0.08	0.15
Muslim-minority country	0.02	0.04	0.02	0.08
Total number of households	8,419	759	9,000	178

Table showing,by each type of migrant household, the means of the PSU-level leave-one-out average of migrant household of each type. The sample is restricted to households who have at least one child.

Table A2: Main Effects and Interaction Effects of Migration on Madrasa Schooling

Panel A: Madrasa schooling of male children	A male child goes to a madrasa	Household sends at least one male child to a madrasa
	(1)	(2)
	2SLS	2SLS
Household has a migrant in a		
Muslim-majority country*Muslim-minority country	1.525	1.805
	(1.099)	(1.625)
Household has a migrant in a		
Muslim-majority country	0.154**	0.117*
	(0.066)	(0.060)
Muslim-minority country	-0.536	-0.359
	(0.416)	(0.426)
Sub-district fixed effect	Yes	Yes
Sample mean	0.07	0.05
N	5,473	6,492

Panel B: Madrasa schooling of female children	A female child goes to a madrasa	Household sends at least one female child to a madrasa
	(1)	(2)
	2SLS	2SLS
Household has a migrant in a		
Muslim-majority country*Muslim-minority country	3.168	0.754
	(4.504)	(1.050)
Household has a migrant in a		
Muslim-majority country	-0.065	0.027
	(0.116)	(0.049)
Muslim-minority country	-0.008	-0.107
	(0.306)	(0.344)
Sub-district fixed effect	Yes	Yes
Sample mean	0.06	0.04
N	5,416	6,183

All the regressions include the following control variables: whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim,whether the household has any member who was abroad for more than six months during the last five years and returned, dummy variables for the level of education of the household head. Column 1 also includes age and square of age. Column 2 for each panel is restricted to households that have at least one child of the sex that the dependent variable is referring to. Standard errors, clustered at PSU level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Relationship between Madrassa Education and Labor Market Outcomes for Population of Ages 15-64 Years

Panel A: Labor market outcomes of males						
	Labor Force Participation=1			Currently Employed=1		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrassa=1	-0.041**	-0.039**	-0.036**	-0.043**	-0.041**	-0.036**
	(0.017)	(0.017)	(0.016)	(0.018)	(0.018)	(0.017)
Fixed effect		Sub-District	PSU		Sub-District	PSU
Comparison group mean	0.83	0.83	0.83	0.83	0.83	0.83
N	16,165	16,165	16,165	16,165	16,165	16,165

Panel B: Labor market outcomes of females						
	Labor Force Participation=1			Currently Employed=1		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrassa=1	-0.014	-0.013	0.001	-0.014	-0.013	0.002
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
Fixed effect		Sub-District	PSU		Sub-District	PSU
Comparison group mean	0.11	0.11	0.11	0.10	0.10	0.10
N	17,236	17,236	17,236	17,236	17,236	17,236

All the regressions include the following control variables: age of the individual in years, square of the age, whether the individual is still attending school, dummy variables for marital status of the individual, whether the household has sent a migrant in a Muslim-majority country in the last five years, and whether the household has sent a migrant a Muslim-minority country in the last five years. Standard errors, clustered at PSU, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Estimation of Individual-Level Effects Using the 2016 round of the Bangladesh Household Income and Expenditure Survey

Panel A **Dependent variable: Goes to a madrasa**	A child		A male child		A female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	0.018***	0.171***	0.018**	0.167***	0.019**	0.175***
	(0.006)	(0.044)	(0.008)	(0.054)	(0.007)	(0.045)
Muslim-minority country	-0.005	0.057	-0.008	0.082	-0.003	0.043
	(0.009)	(0.176)	(0.014)	(0.220)	(0.013)	(0.165)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.05	0.05	0.06	0.06	0.04	0.04
N	49,788	49,788	25,527	25,527	24,261	24,261

Panel B **Dependent variable: Goes to school**	A child		A male child		A female child	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Household has a migrant in a						
Muslim-majority country	0.023***	0.045	0.020***	0.009	0.025***	0.081**
	(0.005)	(0.033)	(0.007)	(0.046)	(0.006)	(0.037)
Muslim-minority country	0.011	0.164	0.017	0.230	0.003	0.095
	(0.011)	(0.129)	(0.014)	(0.180)	(0.015)	(0.115)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.88	0.88	0.87	0.87	0.89	0.89
N	56,439	56,439	29,307	29,307	27,132	27,132

All regressions include the following control variables: age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head was a Muslim,whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Estimation of Household-Level Effects Using the 2016 round of the Bangladesh Household Income and Expenditure Survey

Panel A						
Dependent variable: Household sends to a madrasa						
	At least one child		At least one male child		At least one female child	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Household has a migrant in a						
Muslim-majority country	0.023***	0.220***	0.018**	0.176***	0.020***	0.177***
	(0.007)	(0.050)	(0.008)	(0.051)	(0.007)	(0.044)
Muslim-minority country	-0.001	-0.036	-0.010	0.019	0.004	0.061
	(0.013)	(0.210)	(0.014)	(0.203)	(0.015)	(0.187)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.07	0.07	0.07	0.07	0.04	0.04
N	32,204	32,204	22,043	22,043	20,705	20,705

Panel B						
Dependent variable: Household sends to a non-madrasa school						
	At least one child		At least one male child		At least one female child	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Household has a migrant in a						
Muslim-majority country	0.002	-0.033	0.004	-0.101*	0.010	-0.030
	(0.007)	(0.043)	(0.010)	(0.059)	(0.009)	(0.049)
Muslim-minority country	0.032***	0.137	0.047***	0.201	0.016	0.073
	(0.012)	(0.168)	(0.017)	(0.229)	(0.017)	(0.184)
Sub-district fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	0.89	0.89	0.85	0.85	0.88	0.88
N	32,204	32,204	22,043	22,043	20,705	20,705

All regressions include the following control variables: if the household has an adult above 23 years of age who went to madrasa, whether the household head was a Muslim,whether the household has any member who was abroad for more than six months during the last five years and returned, and dummy variables for the level of education of the household head. Columns 1 and 2 are restricted to households that have at least one child of any sex. Columns 4-6 are restricted to households that have at least one child of the sex that the dependent variable is referencing to. Standard errors, clustered at PSU level, in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Equations for Household Level Analysis

The first-stage regressions:

$$M^1_{hps} = \sigma_s + \sigma_1 Z^1_{p_{(h)}s} + \sigma_2 Z^2_{p_{(h)}s} + \sigma_3 H_{hps} + \phi_{hps} \tag{B1}$$

$$M^2_{hps} = \tau_s + \tau_1 Z^1_{p_{(h)}s} + \tau_2 Z^2_{p_{(h)}s} + \tau_3 H_{hps} + \kappa_{hps} \tag{B2}$$

The second stage is:

$$Y_{hps} = \pi_s + \pi_1 \widehat{M^1}_{hps} + \pi_2 \widehat{M^2}_{hps} + \pi_3 H_{hps} + \omega_{hps} \tag{B3}$$

Exclusion Bias

Table B1: Example of Exclusion Bias

PSU	HH	M^1_{hps}	$Z^1_{p_{(h)}s}$
1	1	0	0
1	2	0	0
1	3	0	0
2	1	0	0.5
2	2	0	0.5
2	3	1	0
3	1	0	1
3	2	1	0.5
3	3	1	0.5