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

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Abstract

This paper investigates whether international migration affects religiosity in the home country. Using a neighborhood-level concentration 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 the 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 socio-economic returns to international migration.

JEL Codes: F22, J11, J61, O15, and Z12
Keywords: International migration, social remittances, religiosity, religious schooling, 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 sent US $529 billion as foreign remittances to low- and middle-income countries (except China) in 2018—an amount higher than total foreign direct investment inflows to these countries (World Bank, 2019). International migrants also transfer *social remittances*—that is, norms and institutions—from the host country (the country of a migrant's destination) to the home country (the country of a migrant's origin).[1] Social remittances can affect the behavior of migrant households (households that send a migrant abroad but live in the home country). Ignoring the implications of social remittances can bias the estimates of the socio-economic returns to international migration for the home country.

This paper addresses the question of whether international migration can affect religious preferences in the home country through social remittances. Religiosity has significant socio-economic effects. For instance, religiosity positively affects income (Bryan et al., 2018) and educational attainment (Gruber, 2005). Religiosity also adversely affects birth outcomes (Almond and Mazumder, 2011), labor supply (Berman, 2000) and increases an individual's tendency to discriminate (Lavy et al., 2018). Consequently, a change in religious preferences through international migration can alter the behavior of a household in a manner that can affect the returns to migration.

This paper estimates the causal impact of a household from Bangladesh sending a migrant abroad on the migrant household's likelihood of sending a child to an Islamic school (*madrasa*) and establishes that the mechanism behind this increase in madrasa schooling is a change in religiosity through a transfer of norms by the migrant.[2] Madrasas have grown faster than any other institution in the education sector of Bangladesh (Asadullah

[1] See Levitt (1998) for details on the origin of the term "social remittances."

[2] The existing literature finds that a household's religiosity affects its choice to send a child to religious schools (Cohen-Zada and Sander, 2008; Sander, 2005).

and Chaudhury, 2008). On the other hand, Bangladesh is a major migrant-sending country and received foreign remittances in 2018 that was equivalent of 5.4% of the country's gross domestic products (GDP) (World Bank, 2019). These conditions make Bangladesh an ideal setting for this study. I use the 2010 round of the Bangladesh Household Income and Expenditure Survey (HIES) for my analysis.

I find that sending a migrant to a Muslim-majority country increases the likelihood of madrasa schooling of a male child of the migrant household by reducing enrollment in non-madrasa schools. Sending a migrant to a non-Muslim-majority country does not have a statistically significant effect on madrasa enrollment for any child of the household. In addition, sending a migrant abroad does not affect general school enrollment.

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—as an instrument. I follow (Fruehwirth et al., 2019) in constructing the instrument.[3] Essentially, I am leveraging on migrant networks which previous studies have used as instrument for migration (Lokshin and Glinskaya, 2009; McKenzie and Rapoport, 2007, 2011). 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 non-Muslim-majority country. My estimates are local average treatment effects (LATE) since I am using an instrumental variables approach (Imbens and Angrist, 1994).

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. I 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. I implement the Olea and Pflueger (2013) weak-instrument test and rule out that my instruments are weak.

I decompose the exclusion restriction into three parts following the strategy of Fruehwirth

[3]Fruehwirth et al. used average peer religiosity as an instrument to estimate the causal impact of religiosity on depression.

et al. (2019)—an individual-specific components, a household-specific components, and a PSU-specific components—and show that the violation of the exclusion restriction through any of these components is unlikely. The violation of exclusion restriction through individual-specific components can occur if there is a violation of exclusion restriction through the household-specific components, since both migration and madrasa schooling is a household-level choice. The household-specific components might cause a violation of the exclusion restriction if a household makes a strategical change of location to facilitate external migration. Since it is costly to migrate and credit constraint limits the migration of household in Bangladesh (Bryan et al., 2014; Mendola, 2008), such strategical movement, and therefore, a violation of the exclusion restriction through household-specific components is implausible. I use robustness tests to argue that a violation of the exclusion restriction through the PSU-specific components of the error term is unlikely. The PSU-specific components might compromise the identification assumption if PSU-level unobservables that vary within the sub-district are correlated with the instruments and outcomes. I find that the causal estimates are robust to the inclusion of the PSU-level leave-one-out average of the outcome and control variables, suggesting that PSU-level confounding variables are unlikely to compromise the validity of the exclusion restriction.

Since the exclusion restriction can be violated through other potential channels, I show that the findings are also robust when I allow a minor relaxation of the strict exogeneity assumption following Conley et al. (2012). That is, my findings remain robust if there is a very small correlation between the instruments and the error term in the second stage.

The increase in madrasa schooling as a result of migration intensifies over time. Using the 2016 round of the HIES, I find that migration increases the likelihood of madrasa schooling for female children, while the effect size for male children is larger than that of 2010. A rise in the school enrollment can partly explain why the madrasa education of female children increased. However, there is no change in the school enrollment of male children.

I rule out financial remittances and learning channel effects as potential mechanisms and show that the most plausible mechanism of the increase in madrasa schooling is a change in religiosity through social remittances. The effects of financial remittances can be separated into income effect and reduction of credit constraint. I rule out an income effect

as the demands for madrasas have lower income elasticity than non-madrasa schools, and rule out reduction of credit constraint as madrasas are cheaper and of lower returns (Al-Samarrai, 2007; Asadullah et al., 2019; Asadullah and Chaudhury, 2010, 2016; Berman and Stepanyan, 2004; World Bank, 2010). Moreover, households with migrants in non-Muslim-majority countries do not send their children to madrasas more—though they would also receive financial remittances—corroborating the inconsistency of financial remittances as the mechanism. I also rule out learning about how madrasa schooling can improve migration opportunities as the potential mechanism based on two facts. First, the quality of education at the madrasas does not enable students to learn Arabic properly (Antara, 2019; Bhuiyan, 2018). Second, madrasa schooling is not a binding constraint to migrate to and work in the Persian Gulf, as manifested by citizens from countries like India, the Philippines, and Sri Lanka having a significant presence and earning potential in the region (Naufal, 2011; World Bank, 2019).

I find evidence to support the consistency of an increase in religiosity. Only the above-median income households are more likely to send their male children to madrasas. Since the returns to madrasa schools are lower, sending children to madrasas would entail forgoing potential future income gains from non-madrasa education. As wealthier households can afford to choose more religious activity over higher future income, this finding is consistent with the social remittances mechanism. This is also consistent with the finding that people may choose religious activity over income generating activity (Berman, 2000).

This paper makes two major contributions. First, it contributes to the literature that studies transfer norms and institutions to the home country by migrants. This paper establishes that international migrants affect religious preferences in the home country—a relationship that has not been much studied. Tuccio and Wahba (2018) show that Jordanian return migrants from Arab countries cause a transfer of conservative gender norms, but they do not attribute this to a change in religiosity.[4] Other researches examine 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; Docquier et al.,

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

2016; Mercier, 2016; Pfutze, 2012; Spilimbergo, 2009; Tuccio et al., 2019), a change in fertility norms (Beine et al., 2013; Bertoli and Marchetta, 2015), and a reduction in widespread social practices such as female genital mutilation (Diabate and Mesplé-Somps, 2019) in the home country. This paper also relates to the broader literature of migration-induced social remittances that includes studies that investigate migrants importing norms to the host country (Alesina et al., 2013; Fernández, 2011; Fisman and Miguel, 2007; Forrester et al., 2019).[5]

Second, this paper contributes to the literature that examines the returns to migration. International migration has direct effects on poverty reduction (Bertoli and Marchetta, 2014), education (Antman, 2011, 2012; Theoharides, 2018), human capital formation (Dinkelman and Mariotti, 2016), labor market outcomes (Binzel and Assaad, 2011; Nguyen and Winters, 2011), technology transfer (Kerr, 2008), and political change (Karadja and Prawitz, 2019).[6] International migration increases migrants' income (Clemens, 2013; McKenzie et al., 2010), who remit money to the home country (Yang, 2008). Remittance income reduces poverty (Adams and Cuecuecha, 2013; Adams and Page, 2005) and child labor (Cuadros-Menaca and Gaduh, 2019), and increases human capital formation (Ambler et al., 2015; Yang, 2008) in the home country. In contrast, this paper shows that with more migration, the economy loses future productivity due to the rise in the number of poorly trained madrasa students. An increase in madrasa schooling can also increase inequality as madrasa students will face an adverse labor market situation compared to their peers in the non-madrasa schools. The results of this paper indicate that the returns to migration may be overestimated if social remittances are unaccounted for.

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 and discussed in Section 5. Section 6 concludes the paper.

[5]It should be noted that often a transfer from the home country to the host country is assumed to be of negative consequences. Given the dearth of empirical evidence, Clemens and Pritchett (2019) suggest such assumption is a conjecture.

[6]Karadja and Prawitz argue that the contributing mechanism behind emigration causing political changes in Sweden was the availability of an outside option—that is, migrating to the United States.

2 Madrasa Education in Bangladesh

Primary and secondary education in Bangladesh has three major streams. First, there are Bengali-medium schools that follow the national curriculum. The public schools and a large number of private schools fall under this category. Second, there are some English-medium schools that largely follow a British curriculum. These are private schools and more expensive than any other type of schools. And third, there are madrasas where the primary focus is on the teaching of the Quran, hadith, and other religious lessons.

There are two kinds of madrasas in Bangladesh that provide primary education or above—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 that would teach both religious and secular subjects. Though the Calcutta Madrasa moved from Kolkata to Dhaka after the partition of India, it was not until the early 1980s that Alia madrasas began to spread in Bangladesh (World Bank, 2010). The curriculum of Alia madrasas includes religious subjects (Quran, Islamic jurisprudence, and the Arabic language[7]) and other secular subjects (the Bengali and English languages, math, science).

Qawmi madrasas, on the other hand, are mostly community based and operated by non-governmental entities. They 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[8] (World Bank, 2010). After the British colonized the sub-continent in the 18^{th} 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, which also depends on its ability to hire teachers. Degrees offered by Qawmi madrasas were not recognized by the state until 2017.

[7]The the Arabic language is not a religious subject, it is generally viewed as one in the social context of Bangladesh.

[8]The Mughals ruled South Asia between between the 16^{th} and 18^{th} century.

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 non-religious schools or that households switch schools for their children to madrasas after primary education. Between the year 1998 and 2014, enrollment in the registered secondary madrasas grew by 45% (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 schools are in low supply. There is a positive correlation between the number of Alia madrasas and the number of nonreligious public schools (World Bank, 2010).

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. Instead, it is more likely to be influenced by demand-side factors such as poverty, cost, or preference. The majority of the madrasa-enrolled students comes from poor households (World Bank, 2010). Most of the madrasa enrollment is at Alia madrasas (Asadullah and Chaudhury, 2016). Madrasas are also cheaper than the non-madrasa alternatives (Asadullah et al., 2015). Qawmi madrasas are always cheaper than Alia madrasas. While the share of private cost for schools run by non-governmental organizations or the government can be less for primary education, Alia madrasas are cheaper than non-religious schools at the secondary level (Al-Samarrai, 2007; Asadullah and Chaudhury, 2016).

Madrasa students face at least two structural issues that adversely affect their labor market potential and put them in a disadvantaged 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 poor 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 stu-

dents are worse than those of their counterparts at secular schools (World Bank, 2010). 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 universities 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 graduates manifest significantly higher fertility rate (Berman and Stepanyan, 2004). Madrasa schooling is also 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 to alleviate poverty, to increase female empowerment, or even to curtail the threat of religious extremism. It should be noted that madrasa students also face a lot of stereotypes that are not true. In Pakistan, madrasa students are more trusting towards non-madrasa students, while their trustworthiness is often under-estimated by those without a madrasa education (Delavande and Zafar, 2015). It is possible that stereotype and stigma against madrasa students might influence their adverse labor market outcomes.

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 may reduce the returns to migration.

3 Data and Descriptive Statistics

For my primary analysis, I use the 2010 round of the HIES—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 PSU, and all members of a household were interviewed.[9]

The key independent variable of interest is whether the household has sent 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 migrant in a Muslim-majority country. I refer to these households as M^1 households. I use membership in the Organisation of Islamic Cooperation and having a majority Muslim population as criteria for a country being a Muslim-majority one (Organisation of Islamic Cooperation, 2019). The Muslim-majority countries that the households in my sample have sent migrants to are: Brunei, Iran, Iraq, Jordan, Kuwait, Libya, Malaysia, Oman, Qatar, Saudi Arabia, Turkey, and the United Arab Emirates. Similarly, I consider a household to have a migrant in a non-Muslim-majority country if that household has sent a migrant to a non-Muslim-majority country and refer to that as M^2 households. The non-Muslim-majority countries that the households in my sample have sent migrants 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 limitations to this approach of measuring migration. First, the HIES does not collect any information on exactly when the migration occurred. Therefore, I cannot measure the length of the period that the migrant has been away from home. I can only take an extensive margin of migration. I cannot measure the intensive margin, the length of the time 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 migration

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

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 has returned from abroad within the last five years after living their for at least six months, 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 effects of return migration. I can only identify the total effect of any migration—first time or repeat—that has happened in the previous five years, irrespective of whether the migrant has returned home or not.

As the primary outcome of interest in this paper is the likelihood that a household sends a child to a 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 effects. I consider a household to be a madrasa-sending household if at least one child of the household goes to a madrasa. For the household-level analysis, I restrict my sample to households that have at least one child. These restrictions reduce my sample to 9,178 households and 18,063 children in the 2010 round, and to 56,439 children in 32,204 households in the 2016 round of the HIES. In the HIES 2010, there are 1,578 children from 758 M^1 households and 357 children from 178 M^2 households, while there are 3,707 children from 2,114 M^1 households and 863 children from 469 M^2 households in the HIES 2016.

Table 1 reports the descriptive statistics of the key outcome variables in the HIES 2010.[10] About 5% of the children from M^1 households attend madrasas, compared to 4% of children from non-migrant households. In addition, M^1 households are more likely to send at least one of their children to a madrasa than are non-migrant households. Eight percent of M^1 households send at least one child to a madrasa, while 6% of households without a migrant in a foreign 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-migrant household 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 migrant household doing so (6%).

[10]Table A1 in Appendix A reports the descriptive statistics of these variables in the HIES 2016.

Table 2 reports the descriptive statistics for several individual- and household-level variables.[11] In the estimation sample, 52% of the children are male and the average age 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%), likewise the majority are headed by 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 madrasa (2%). This alludes to the fact that the increase in madrasa education is a recent phenomenon, correlated with the rise in school enrollment in Bangladesh. Roughly 1% of the households have a member who had returned from abroad in the last five years after living there for at least six months.[12]

4 Empirical Strategy

4.1 Estimation Method

Let i indicate a child, 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 child i of household h in PSU p of sub-district s goes to a madrasa, and 0 otherwise. M^1_{hps} is an indicator for 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 non-Muslim-majority 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 term. 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 in preferences for households who would not send any child to a madrasa otherwise, I also perform a household-

[11] Table A2 in Appendix A reports the descriptive statistics of the these variables in the HIES 2016.

[12] Note that there is no information on when these members migrated abroad and to which countries they migrated. In relation to their timing of return, the only thing that can be ascertained is that they returned home within the last five years.

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 estimating these equations is that international migration is not a random phenomenon, that is, $cov(M^j_{hps}, \xi_{ihps}) \neq 0$ or $cov(M^j_{hps}, \zeta_{hps}) \neq 0$ 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, ordinary least squares (OLS) will produce biased estimates due to omitted variables bias. The wealth of the household cannot be included in the estimation, while its exclusion can create further endogeneity issues. The wealth of a household can have a simultaneous relationship with the school that a child of that household attends. A potential change in the wealth of the household can influence the attainment of education. With an increase in wealth from migration, households might decide to send their children to school (that is, the extensive margin of schooling). Wealthier households might also choose to send their children to more expensive schools. On the other hand, the returns to education of a child would affect household wealth. Hence, there is a simultaneous relationship between schooling and household wealth. In addition, while a household's decision to send a migrant abroad may depend on the wealth of that household (McKenzie and Rapoport, 2007), migration itself can improve the wealth of the household. Therefore, wealth cannot be included in the equation. But exclusion of wealth that also introduces omitted variable bias into the estimation strategy. In addition to wealth, the level of education of the migrant, intra-household power dynamics can act as confounding factors for migration and school choice.

To overcome the endogeneity of migration and schooling, I use an instrumental variables method. I use the leave-one-out fraction of migrant households in a PSU as the instru-

mental variable. 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 instrumental variables. 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 a household h of migration type M^j in a PSU p of sub-district s, the instrumental variable is defined as:

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

Here, N is the total number of households in the PSU. 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; McKenzie and Rapoport, 2007; 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 a madrasa. Since migration is a binary variable, there are only two values for each of the instruments within each PSU—one value if the household is a migrant household, and another if not. Hence, most of the variation in the instrumental variables comes from between PSU variation. Table A3 in Appendix A reports the descriptive statistics of the instrumental variables.

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.[13] Thus, β_1 and β_2 from a two-staged least squares (2SLS) estimation are consistent estimates of the parameters of interest.[14] As the sampling strategy involved picking PUSs randomly and then interview randomly chosen households, I cluster standard errors at the PSU level—following Abadie et al. (2017).

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 a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, the level of education of the household head, and sub-district-level fixed effects. I include all but the individual-level controls (age in years and age squared) as control variables for the household-level analysis.

4.2 Identification

I exploit the variation in the 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. The underlying assumption is as follows: 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

[13] These first-stage estimates suffer from problems elucidated in Manski (1993). However, following Fruehwirth et al. (2019), I argue that these problems do not threaten my identification since I am interested in the correlation in the first stage, not causation.

[14] The first- and second-stage equations for the household-level estimates are presented in Appendix C.

decision for a child. Formally, my identification relies on the following assumptions:

$$\lambda_1 \neq 0 \ \& \ \gamma_2 \neq 0 \tag{A1}$$

$$Cov(Z^j_{p_{(h)}s}, \epsilon_{ihps}) = 0 \ \ \forall j \in \{1, 2\} \tag{A2}$$

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 non-Muslim-majority 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. A household's own probability of sending a migrant to a Muslim-majority country increases by 68.3 percentage points when the fraction of households in the neighborhood with a migrant in a Muslim-majority country increases from 0 to 1. When there is a similar increase in the fraction of households with a migrant in a non-Muslim-majority country, the probability of a household to send a migrant in those countries increases by 40.7 percentage points. The strong and statistically significant estimates of the instruments for both types of migrant-households imply that the instrumental variables satisfy the relevance condition (assumption A1). Using the weak instrument test of Olea and Pflueger (2013), I find that the Olea-Pflueger F-statistics for $Z^1_{p(h)s}$ and $Z^2_{p(h)s}$ are higher than the critical values for 5% and 10%, respectively, of the worst-case bias from a weak instrument. Therefore, I can rule out that the instrumenta are weak.

One major threat to identification is the violation of assumption A2—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 house-

hold'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 migrants across PSUs may violate the exclusion restriction, I divide the residuals from the second stage into three parts following the strategy of Fruehwirth et al. (2019): individual-specific components (u_{ihps}), household-specific components ($v_{h(i)ps}$), and PSU-specific components ($\nu_{p(h)s}$) that include PSU-level direct effects on school choice or other PSU-level unobservables. As a result, the error term can be written as $\epsilon_{ips} = u_{hps} + v_{h(i)ps} + \nu_{p(h)s}$. Assumption A2 can be written as follows:

$$Cov(Z^j_{p(h)s}, u_{hps} + v_{h(i)ps} + \nu_{p(h)s}) = Cov(Z^j_{p(h)s}, u_{ihps}) +$$
$$Cov(Z^j_{p(h)s}, v_{h(i)ps}) + Cov(Z^j_{p(h)s}, \nu_{p(h)s}) = 0$$

For the estimates to be consistent, the following conditions need to be true:

$$Cov(Z^j_{p(h)s}, u_{ihps}) = 0 \tag{A2$'$}$$

$$Cov(Z^j_{p(h)s}, v_{h(i)ps}) = 0 \tag{A2$''$}$$

$$Cov(Z^j_{p(h)s}, \nu_{p(h)s}) = 0 \tag{A2$'''$}$$

Conditions A2$'$ or A2$''$ are violated when an individual or a household can select into PSUs based on unobservables which are related with both madrasa education and migration. Such selection will not be addressed by sub-district-level fixed effects. Since a systematic change of PSU by a child is not a practical reality, we can assume that such violation would occur only through a systematic change of PSU by households. Moreover, both the key independent variable—whether a household sends a migrant abroad—and the key outcome variable—the decision of sending any child to a madrasa—are household level decisions. Therefore, for all

the intents and purposes, I can argue that condition A2′ will be violated if A2″ is violated.

For a violation of $Cov(Z^{j}_{p(h)s}, v_{h(i)ps}) = 0$, a household would have to systematically change PSU based on the fraction of migrants there are or based on anything that is correlated with the fraction of migrants and choice of school type. In other words, 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 is unlikely in this setting 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, is does not seem plausible that Bangladeshi households would strategically move into different PSUs that would facilitate international migration rather than migrating to areas with higher wage jobs. Hence, I do not consider that such a violation of condition A2″ is a likely threat.

Condition A2‴ 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 PSU-level observables or unobservables that affect sending a child to a madrasa and also correlate with the fraction of migrants in the PSU. 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 estimates do not change when PSU-level observables are controlled for. If the estimates were driven by unobservable 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

The primary equation that I estimate is equation 5:

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

Results from estimation of this equation—presented in Table 4—show that a child from a household with a migrant in a Muslim-majority country (M^1) is 6 percentage points more likely to go to a madrasa. A 6 percentage points increase is equivalent of a 150% increase in the probability compared to the sample mean. The effect on the probability that a child from a household with a migrant in a non-Muslim-majority country (M^2) goes to a madrasa is negative is magnitude, but not statistically significant.

The LATE estimates from the second-stage are larger than the OLS estimates. This suggests that the naive estimates are biased downward. Omitted variables—such as, household wealth, aspiration of earning higher income, skill and ability of the migrant—would create a downward bias. These omitted variables would positively correlate with the likelihood of migration, but are likely to have a negative correlation with the preference for a school that has relatively lower returns (Asadullah and Chaudhury, 2010; World Bank, 2010).

This result is driven by the causal impact of a household sending a member to a Muslim-majority country on the probability of that household sending a male child to a madrasa. A male child from an M^1 household is 10.8 percentage points more likely to be sent to a madrasa. In other words, if a member migrates to a Muslim-majority country, it increases the household's probability to send a male child to madrasa by 2.5 times of that of the sample mean. As with the estimates for a child of any sex, the magnitude of the impact of having a migrant in a non-Muslim-majority country on the likelihood of male child being sent to madrasa is negative and statistically insignificant. The estimates of the effects of being an M^1 or M^2 household on the likelihood of sending a female child to a madrasa are very small (0.003 and 0.008, respectively) and statistically insignificant.

M^1 households send some of their children to madrasas whom they would have other-

wise sent to non-madrasa schools had there been no migration. The results presented in Table 5 show that having a migrant abroad does not have a significant impact on increasing enrollment to school. Add to that, the direction of the effect of having a migrant in a Muslim-majority country on the likelihood of sending a male child to a non-madrasa school is negative (-0.136)—though, due to relatively large standard errors (0.096), the effect is not significant at a 10% level of significance. However, this result suggests that the increase in the likelihood of madrasa schooling for male children is due to households switching from non-madrasa schools to madrasas; not because of a general increase in school enrollment.[15]

Having a migrant in a Muslim-majority country also affects whether the household sends at least one child to a madrasa (10.2 percentage points 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 (12.9 percentage points increase). Panel A of Table 6 reports the results for this estimation. 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.

Since the dependent variable here is whether the household sends at least one child to a madrasa, the household-level effects indicate that sending a migrant abroad can also increase madrasa schooling at the extensive margin. That is, migration of a member of the household to a Muslim-majority country causes a household to send at least one child to a madrasa, while that household would not have sent any child to a madrasa in absence of sending a member abroad. As there is no increase in schooling as a whole, this increase at the extensive margin further corroborates that the effect I find is a switching effect.

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 results presented in Panel B of Table 6 show that having a migrant abroad does not have a statistically significant effect on the likelihood of sending at least one child to a non-madrasa school. The effect of having a migrant in a Muslim-majority country on the likelihood of

[15]To further verify that the effect is driven by switching away from non-madrasa schools to madrasa schools, I estimate how migration affects choice of schooling conditional on enrollment to school. The results presented in Table A4 in Appendix A show that migration of a household member to a Muslim-majority country causes an increase in the likelihood of that household sending a male child to a madrasa by 16.7 percentage points.

sending at least one male child to a non-madrasa school has a sizable but imprecise negative estimate. Similarly, having a migration in a non-Muslim-majority country has a statistically insignificant but sizable positive estimate for the effect on sending at least one male child to a non-madrasa school. There is no impact when I look at the likelihood of sending at least one female child to a non-madrasa school, either.[16]

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 not for all of them. As indicated above, the existing literature suggests that madrasa students have worse learning outcomes (World Bank, 2010) and lower returns to education (Berman and Stepanyan, 2004) than non-madrasa students. 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.

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 force participation and current employment. Table 7 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 3.5-4 percentage points, depending on the specification. The employment rate also declines by about 3.5-4.2 percentage points. The reduction of labor force participation and current employment indicates that madrasa educated males are relatively worse off than the non-madrasa-educated males in terms of their labor market outcomes.

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.[17] Since external migration

[16]To observe the joint effect of M^1 and M^2, I re-estimate the equations of interest including an interaction of M^1 and M^2. The results are reported in Table A5 in Appendix A. The interaction terms are not statistically significant for any of the specifications.

[17]The concern of adverse influence in the human capital production is amplified by the likelihood that stereotype and stigma against the madrasa-graduates (Delavande and Zafar, 2015) may contribute to the creation of an unfavorable labor market situation for them.

is extremely important due to the large welfare gain it can generate (Clemens, 2011), if the reduction in human capital is unaccounted for, then the calculated return of external migration would be overestimated. This indicates that, the actual return is less than what we have so far thought it is.

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 disadvantaged position in terms of earning potential relative to their peers at non-madrasa schools. This may further exacerbate inequality in society. While international migration can enhance welfare, a systematic increase in madrasa education would reduce the returns to migration. Hence, these findings provide 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 $Cov(Z^j_{p(h)s}, \nu_{p(h)s}) = 0$ 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 control 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 the level of education of the household head. I also include the leave-one-out mean of the outcome variable, that is the fraction of children in the PSU that attends a madrasa. Then I estimate the equation with both the pre-determined neighbor characteristics and outcomes. Table 8 reports the results of the estimation.

I find that an inclusion of the neighbor characteristics does not change the results, though their magnitude increases slightly (11.4 percentage points). When I include only the average of the neighbors' outcome, again, the magnitude is smaller (8.9 percentage points)—but qualitatively, the results remain the same.[18] When I include both the neighbor characteris-

[18]The drop in the magnitude is expected given the mechanical negative bias that leave-one-out means create—referred as "exclusion bias" by Caeyers and Fafchamps (2016) . For illustration purposes, consider

tics and the neighbor outcome, the estimates (10.1 percentage points) are almost the same as that of the baseline results (10.8 percentage points). 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 $Cov(Z^j_{p(h)s}, \nu_{p(h)s}) = 0$ and 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.[19]

It is possible that there are other reasons that violate the exclusion restriction that I have not thought of. Hence, I check whether my results are robust to a relaxation of the strict exogeneity conditions following the methodology laid out by Conley et al. (2012). 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. 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 follow Nunn and Wantchekon (2011) and Azar et al. (2017) to implement this methodology. I regress madrasa schooling 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 the probability of madrasa schoolings, I focus on the effects of M^1 when I assume plausible exogeneity of Z^1. The coefficient of Z^1 is 0.067 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 0.067 and the lower bound is zero.[20] The results of this computation

Table C1 in Appendix C. Due to the exclusion bias, my first stage estimates are potentially downward biased as well. Again, it does not posit a threat to my identification as I am interested in the correlation in the first stage, not causation.

[19]The stability of results after inclusion of neighbor outcome and characteristics also suggests that migration status of neighbor household is unlikely to affect own outcome - a concern raised by Betz et al. (2018) about spatial instruments.

[20]Assuming negative values for β_{Z^1} does not threaten my results as, when I assume β_{Z^1} to be negative,

are reported in Table 9.

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 approximately 0.012, which is roughly 6.3% of the upper bound of β_{Z^1} (0.19). This means that my main results are robust for a minor violation of the strict exogeneity assumption.

5.2.2 Intertemporal external validity

To verify whether the results hold over time, I estimate my main results using the HIES 2016. The HIES 2016 was collected based on a new sample. If the results of the HIES 2010 and 2016 were inconsistent, that would raise doubts about the validity of the findings.[21]

Table 10 presents the results of the estimation of my main specification (equation 5) using the 2016 round of the HIES. The new estimates show that having a migrant in a Muslim-majority country increases the likelihood of sending a child to a madrasa by 15.4 percentage points as opposed to 6 percentage points in 2010. In 2016, the point estimate of the effects on the likelihood of sending a male child to a madrasa is 0.147, as opposed to 0.108 from 2010. Moreover, the probability of sending a female child to a madrasa also increases by 4 times the sample mean in 2016.[22] Migration to a non-Muslim majority country, similar to the results I find using the HIES 2010, does not have a statistically significant effect on the likelihood of sending any child or a child of a particular gender to a madrasa.

To further verify whether the results are intertemporally consistent, I use the HIES 2016 to estimate the effects of migration on school enrollment and on non-madrasa schooling. Results from Table A8 in Appendix A show that migration to a Muslim-majority country reduces the probability of a male child going to a non-madrasa schools by 13.8 percentage points, or in other words, 17% than that of the sample mean. Migration to a non-Muslim-

the estimates for β_1 are always positive and the confidence intervals do not include zero.

[21] The first-stage estimates using the 2016 round of the HIES are reported in Table A6 of Appendix A. Estimates show that the instruments are relevant. In addition, from the Olea-Pflueger test, I can rule out that there is a weak-instruments problem.

[22] Table A7 in Appendix A shows the estimates from pooling the 2010 and 2016 rounds of the HIES. This indicates that the increase in madrasa schooling in 2016 is driven by the increase in madrasa schooling of female children.

majority country, on the other hand, does not have a statistically significant effect on the likelihood of non-madrasa schooling. Results form the household-level analysis using the HIES 2016—presented in Table A9 in Appendix A—are qualitatively similar to the results that I find from using the HIES 2010. The only meaningful difference is that having a migrant in a Muslim-majority country reduces the likelihood of sending at least one male child to a non-madrasa school. This implies that with the passage of time, migrant households become more likely to send all of their male children to madrasas.

The analysis using the HIES 2016 shows that the intensity of the causal impacts has increased over time. The effects on sending male children to madrasas persist and the point estimate becomes larger. In addition, additional effects on sending female children to madrasas appear to manifest over time. A general increase in female education can partially explain the increase in madrasa schooling for female children. However, there is no general increase in the enrollment of male children. Therefore, the increase in madrasa schooling for male children is not due to an increase in their enrollment.

5.3 Mechanisms

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

I can separate the financial remittances effect into two parts—income effect and reduced credit constraint. If the demand for madrasa has high income elasticity, then the additional household income generated from the financial remittances received from migrants might increase madrasa education. Here, the choice of school is discrete—madrasas or non-madrasa schools. Hence, if there is a high relative income elasticity of madrasa education, then madrasa schooling might increase with migration to Muslim-majority countries. However, in the absence of migration, madrasa education has a lower income elasticity than non-madrasa options. In Figures 1 and 2, I plot the sex-wise probability of a child from a non-migration household to go to a madrasa for different total household income and asset, respectively. The slope for sending a child to a madrasa is lower than the slope for sending a child to a

non-madrasa school. This suggests that given the two choices, madrasa schooling does not have the higher income elasticity. Thus, I can rule out the income effect mechanism.

The mechanism of a reduction of credit constraint would work in the following way: a household, in spite of the willingness to send a child to a madrasa, cannot do so due to not having the means. In the absence of migration the said household would send the child to a non-madrasa school, as otherwise there would have been an increase in school enrollment. If the household's credit constraint is reduced because of financial remittances sent by the migrant, the household decides to send the child to a madrasa.

There are two reasons why this mechanism is inconsistent. First, madrasas in Bangladesh are less expensive than non-madrasas. Qawmi madrasas are cheaper than Alia madrasas, and non-madrasa schools might be much more expensive considering all the outside tutoring fees that a household might have to pay. Admittedly, non-madrasa schools might be a cheaper option than madrasas at the primary level, but at the secondary level madrasas are cheaper than non-madrasa schools (Al-Samarrai, 2007; Asadullah and Chaudhury, 2016). To test if the results are driven by primary school students, I estimate the main specification by slicing the sample according to age group. Table A10 in Appendix A reports the result. Since different children might start primary school at different ages, I split the sample in different ways. It shows that the point estimates are larger and more precise for the age group at which students would go to secondary schools, suggesting that the causal impact is much stronger for madrasa schooling at the secondary level. Hence, it does not make sense that a reduction in the credit constraint would increase madrasa enrollment by reducing non-madrasa schooling, the costlier option.

Second, madrasa schools have lower returns than the non-madrasa schools (Berman and Stepanyan, 2004). Madrasa schools are associated with adverse learning (World Bank, 2010) and labor market outcomes (Asadullah and Chaudhury, 2010). Again, it is not consistent that with the credit constraint relaxed, the migrant households will switch away from the option with higher returns and choose madrasa schools. Hence, the credit constraint reduction mechanism does not explain the results that I find.

I also find that the households who are sending migrants to non-Muslim-majority countries—which are also richer countries, in general—are not sending their children to madrasas. If

an income effect or a reduction of credit constraint was the mechanism behind the increase in madrasa schooling, then households who are sending members to non-Muslim-majority countries would have also had an increased likelihood of sending their children to madrasas. The insignificant effects of migration to non-Muslim-majority countries further corroborate that the effects of financial remittances are not driving the results.

The second potential mechanism is the learning channel effect. 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). Hence, the Arabic learned in the madrasas in Bangladesh is not useful for migrating to Muslim-majority countries.

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 comes 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 financial remittances or learning channel effects, the most plausible mechanism is the effects of social remittances—that is, transfer of religious norms from the host countries that influences religiosity of the migrant households. The significant influence of migration to a Muslim-majority country on increased enrollment in madrasa education must concern the unique aspect that a madrasa offers—religious schooling. Madrasa education is primarily focused on the teaching of religion. Moreover, the causal effect I find is for households that have sent a migrant to a Muslim-majority country. This indicates that a change in religious preferences 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 non-Muslim-majority country further strengthens this argument. Additionally, previous studies on Catholic schools in the United States provides evidence on religiosity influencing a household's decision to send a child to a religious school (Cohen-Zada and Sander, 2008; Sander, 2005).

Since madrasa 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 that sending a child to a non-madrasa school would have provided. I test this implication of the social remittance mechanism by estimating treatment effect heterogeneity by income in Table 11. 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 (19.7 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. Berman (2000) has also reported evidence of people choosing religious activities over income generating activities, however, he does not conclude that such a phenomenon is only true for wealthier households.

The social remittance mechanism is consistent with the existing findings from other social sciences that used qualitative methods. 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 their 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).

Since 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 preferences, 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 cause an increase in the religiosity of the home country. 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 affects religious preferences in the home country through social remittances. I have found that there is a strong migration-induced transfer of religious preferences from Muslim-majority countries to Bangladesh that increases 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 would otherwise

attend non-madrasa schools. 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 increase in madrasa schooling to indicate an increase in religiosity. I address the challenges of using such an indirect measure by considering alternative potential channels and showing that the implications of those channels are inconsistent with my findings. To demonstrate that the most plausible mechanism of international migration causing an increase in madrasa schooling is a transfer of religious preference, I rule out the effects of financial remittances and learning about migration as potential mechanisms.

One key limitation of this paper is that the instrument used is an unconventional one. However, I demonstrated that the implications of the potential violations of the exclusion restriction do not compromise the results. Nonetheless, it is possible that there are other channels through which the exclusion restriction can be violated that I did not consider. To that end, I tested if my results would survive if the strict exogeneity restrictions are violated, and I found that my results are robust to a minor relaxation of the exclusion restriction assumption. Another major limitation is that I could only estimate the local average treatment effects, as I used an instrumental variable approach. Estimating an average treatment effect is recommended for a possible future research agenda.

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, might lead to adverse human capital production in Bangladesh. Hence, an increase in madrasa education could 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. This paper's findings further imply that 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.

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 how social-remittances mechanism might exist in different contexts that also can reduce the returns to migration.

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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	A migrant in a non-Muslim-majority country	No migrant abroad	All households
Individual level				
Goes to madrasa				
A child	0.05	0.04	0.04	0.04
A male child	0.05	0.04	0.04	0.04
A female child	0.04	0.03	0.04	0.04
Goes to non-madrasa school				
A child	0.61	0.63	0.56	0.56
A male child	0.61	0.62	0.54	0.55
A female child	0.61	0.65	0.58	0.58
Does not go to school				
A child	0.35	0.33	0.40	0.40
A male child	0.34	0.34	0.42	0.41
A female child	0.35	0.32	0.38	0.38
Total number of children	1,578	357	16,169	18,063
Household level				
Goes to madrasa				
At least one child	0.08	0.05	0.06	0.06
At least one male child	0.04	0.04	0.04	0.04
At least one female child	0.04	0.03	0.03	0.03
Goes to non-madrasa school				
At least one child	0.77	0.74	0.69	0.70
At least one male child	0.51	0.46	0.44	0.44
At least one female child	0.48	0.49	0.43	0.44
Does not go to school				
Any child	0.20	0.23	0.28	0.27
Any male child	0.46	0.52	0.54	0.53
Any female child	0.49	0.48	0.55	0.54
Total number of households	758	178	8,260	9,178

Table showing the means of the individual- and household-level outcome variables by migration status of a household and for the total estimation sample of the 2010 round of the HIES. 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. Source: Author's own calculated based on the HIES 2010.

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

	Household has			
	A migrant in a Muslim-majority country	A migrant in a non-Muslim-majority country	No migrant abroad	All households
Individual level				
Sex of the child (male=1)	0.52	0.47	0.52	0.52
Average age (in years)				
All children	11.52	11.94	11.22	11.26
All male children	11.44	11.73	11.30	11.32
All female children	11.61	12.13	11.13	11.20
Total number of children	1,578	357	16,169	18,063
Household level				
Household head is				
Male	0.46	0.58	0.91	0.87
Muslim	0.96	0.94	0.88	0.88
Household location				
Metropolitan	0.06	0.02	0.09	0.09
Urban	0.24	0.31	0.27	0.27
Rural	0.70	0.67	0.64	0.64
Household has				
An adult (>23 years old) who went to a madrasa	0.02	0.03	0.02	0.02
A member who returned from abroad in the previous five years	0.04	0.04	0.01	0.01
Education of the household head				
No formal education	0.47	0.39	0.53	0.52
Primary or below	0.19	0.17	0.15	0.16
Secondary	0.30	0.34	0.22	0.23
Post secondary	0.04	0.10	0.10	0.10
Total number of households	758	178	8,260	9,178

Table showing the means of the individual- and household-level characteristics by migration status of a household and for the total estimation sample of the 2010 round of the HIES. 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. Source: Author's own calculated based on the HIES 2010.

Table 3: First-Stage Estimates

	Dependent variable: Household has a migrant in a Muslim-majority country			**Dependent variable: Household has a migrant in a non-Muslim-majority country**		
	Second-stage estimation sample universe:					
	Individual		Household	Individual		Household
	(1)	(2)	(3)	(4)	(5)	(6)
	Male children	Female children	All households	Male children	Female children	All households
The PSU-level leave-on-out fraction of households with a migrant in a						
Muslim-majority country	0.677***	0.622***	0.683***	0.049***	0.055***	0.054***
	(0.045)	(0.043)	(0.036)	(0.016)	(0.019)	(0.014)
Non-Muslim-majority country	0.204***	0.057	0.197***	0.320***	0.527***	0.407***
	(0.072)	(0.087)	(0.062)	(0.080)	(0.121)	(0.093)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr.	0.12	0.11	0.12	0.04	0.06	0.04
Olea-Pflueger F-statistics	183.13	142.78	286.64	18.38	21.17	21.90
Critical Value for 5% of worst case bias	19.81	14.98	18.91	26.43	29.62	29.28
Critical Value for 10% of worst case bias	12.79	9.93	12.25	16.67	18.54	18.33
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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. The Olea-Pflueger F-statistics and 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. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Individual-Level Effects of a Household Having a Migrant Abroad on the Likelihood of Sending a Child to a Madrasa

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 countr	0.003	0.060*	0.005	0.108**	0.002	0.003
	(0.007)	(0.034)	(0.009)	(0.044)	(0.008)	(0.040)
Non-Muslim-majority country	-0.006	-0.060	-0.005	-0.161	-0.006	0.008
	(0.013)	(0.106)	(0.016)	(0.174)	(0.015)	(0.109)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.04	0.04	0.04	0.04	0.04	0.04
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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Individual-level Effect of Household Having A Migrant Abroad on the Schooling Decision of a Child of the Household

	Panel A			*Panel B*			*Panel C*		
	Dependent variable: Goes to a madrasa			**Dependent variable: Goes to any school**			**Dependent variable: Goes to a non-madrasa school**		
	(1) A child	(2) A male child	(3) A female child	(4) A child	(5) A male child	(6) A female child	(7) A child	(8) A male child	(9) A female child
Household has a migrant in a									
Muslim-majority country	0.060*	0.108**	0.003	0.023	-0.027	0.062	-0.037	-0.136	0.059
	(0.034)	(0.044)	(0.040)	(0.081)	(0.090)	(0.098)	(0.085)	(0.096)	(0.104)
Non-Muslim-majority country	-0.060	-0.161	0.008	-0.061	0.126	-0.192	-0.001	0.287	-0.201
	(0.106)	(0.174)	(0.109)	(0.304)	(0.407)	(0.313)	(0.332)	(0.420)	(0.360)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.04	0.04	0.04	0.60	0.59	0.62	0.56	0.55	0.58
N	18,063	9,322	8,741	18,063	9,322	8,741	18,063	9,322	8,741

All coefficients are 2SLS estimates. Each regression includes 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: 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	0.102**	0.002	0.129**	0.007	0.032
	(0.011)	(0.048)	(0.012)	(0.057)	(0.010)	(0.050)
Non-Muslim-majority country	-0.014	0.036	-0.002	-0.124	-0.004	0.039
	(0.015)	(0.164)	(0.021)	(0.206)	(0.018)	(0.153)
Sub-district fixed effects	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***	0.114	0.082***	-0.142	0.035	0.201
	(0.016)	(0.091)	(0.023)	(0.111)	(0.021)	(0.125)
Non-Muslim-majority country	0.019	-0.085	0.058	0.806	0.016	-0.274
	(0.033)	(0.401)	(0.044)	(0.541)	(0.043)	(0.367)
Sub-district fixed effects	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: whether the household has an adult above 23 years of age who went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Relationship between Madrasa 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)
Madrasa=1	-0.040**	-0.038**	-0.035**	-0.042**	-0.040**	-0.035**
	(0.017)	(0.017)	(0.016)	(0.018)	(0.018)	(0.017)
Fixed effects		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)
Madrasa=1	-0.005	-0.006	0.003	-0.006	-0.007	0.004
	(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, dummy variables for the religion 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 in a non-Muslim-majority country in the last five years. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Tests on Neighbor Characteristics Influencing Madrasa Schooling

	(1)	(2)	(3)	(4)
Panel A				
Dependent variable: A male child goes to a madrasa				
	Baseline results	Include Neighbor household controls	Include Neighbor household outcomes	Include Neighbor household controls and outcomes
Household has a migrant in a				
Muslim-majority country	0.108**	0.114**	0.089**	0.101**
	(0.044)	(0.051)	(0.040)	(0.048)
Non-Muslim-majority country	-0.161	-0.211	-0.149	-0.191
	(0.174)	(0.185)	(0.150)	(0.168)
Sub-district fixed effects	Yes	Yes	Yes	Yes
N	9,322	9,322	9,322	9,322
Panel B				
Dependent variable: A female child goes to a madrasa				
	Baseline results	Include Neighbor household controls	Include Neighbor household outcomes	Include Neighbor household controls and outcomes
Household has a migrant in a				
Muslim-majority country	0.003	-0.019	-0.002	-0.019
	(0.040)	(0.045)	(0.029)	(0.038)
Non-Muslim-majority country	0.008	-0.039	-0.001	-0.032
	(0.109)	(0.103)	(0.081)	(0.087)
Sub-district fixed effects	Yes	Yes	Yes	Yes
N	8,741	8,741	8,741	8,741

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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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- whether the household has an adult above 23 years of age who went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and the level of education of the household head. 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. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: 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) 2SLS	(2) 2SLS
The PSU-level leave-on-out fraction of households with a migrant in a		
Muslim-majority country	0.067***	0.089***
	(0.020)	(0.027)
Non-Muslim-majority country	-0.026	-0.012
	(0.048)	(0.065)
Bounds of the coefficient for the household having a migrant in a Muslim-majority country		
Lower bound	-0.083	-0.115
Upper bound	0.194	0.238
$\beta_{Z^1_{max}}$	≈0.012	0.011
Sub-district fixed effects	Yes	Yes
N	9,322	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) 2SLS	(2) 2SLS
The PSU level leave-on-out fraction of households with a migrant in a		
Muslim-majority country	0.001	0.020
	(0.019)	(0.025)
Non-Muslim-majority country	0.008	0.026
	(0.047)	(0.063)
Bounds of the coefficient for the household having a migrant in a Muslim-majority country		
Lower bound	-0.076	-0.097
Upper bound	0.082	0.134
$\beta_{Z^1_{max}}$	N/A	N/A
Sub-district fixed effects	Yes	Yes
N	8,741	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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Individual-Level Effects of a Household Having a Migrant Abroad on the Likelihood of Sending a Child to a Madrasa (Using the HIES 2016)

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***	0.154***	0.017**	0.147***	0.019***	0.160***
	(0.006)	(0.040)	(0.008)	(0.048)	(0.007)	(0.041)
Non-Muslim-majority country	-0.004	0.056	-0.008	0.083	-0.002	0.041
	(0.009)	(0.153)	(0.013)	(0.189)	(0.012)	(0.145)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.05	0.05	0.06	0.06	0.04	0.04
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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU level, in parentheses.Source: Author's own calculated based on the HIES 2016. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

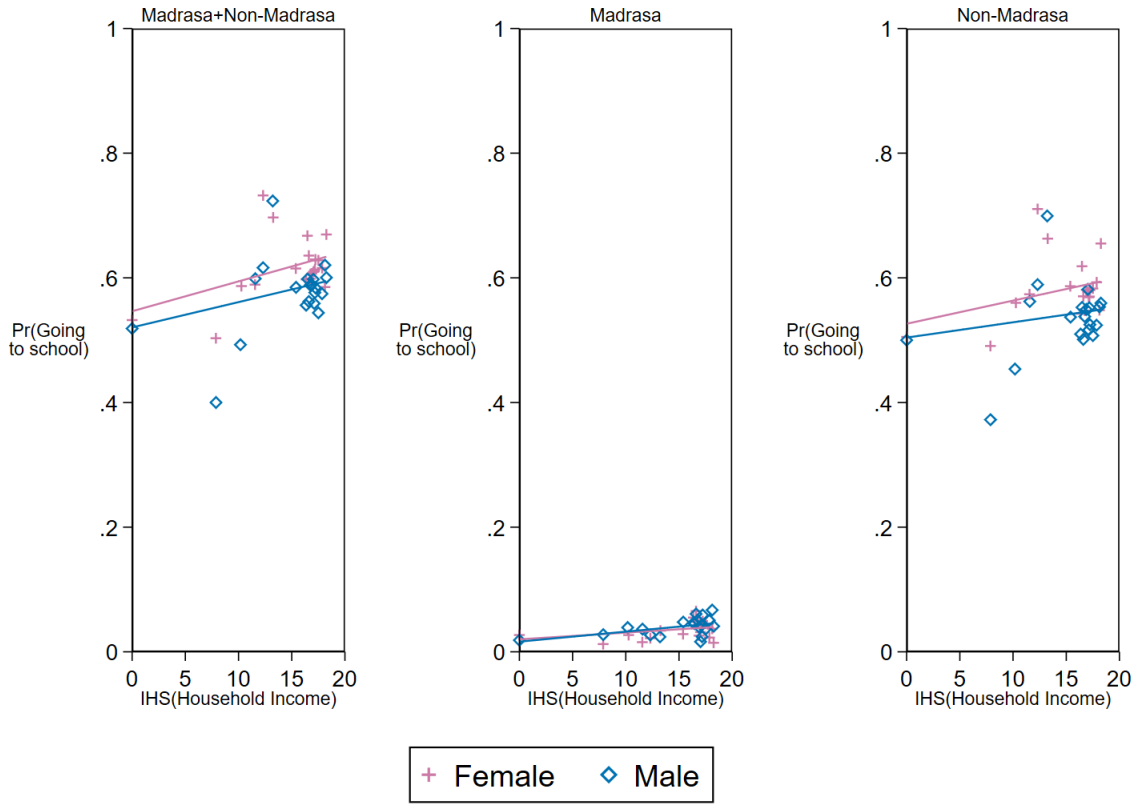
Table 11: Heterogeneous Effects on Madrasa Schooling by Household Income

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	0.065	0.197**	0.071	0.226**
	(0.057)	(0.085)	(0.067)	(0.099)
Non-Muslim-majority country	0.087	-0.734	0.044	-0.456
	(0.175)	(0.614)	(0.185)	(0.615)
Sub-district fixed effects	Yes	Yes	Yes	Yes
Sample mean	0.04	0.04	0.05	0.06
N	4,338	4,983	3,061	3,430
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	-0.016	0.053	0.011	0.091
	(0.047)	(0.075)	(0.057)	(0.101)
Non-Muslim-majority country	0.039	-0.049	0.089	0.004
	(0.140)	(0.285)	(0.180)	(0.437)
Sub-district fixed effects	Yes	Yes	Yes	Yes
Sample mean	0.03	0.04	0.04	0.05
N	4,093	4,646	2,948	3,233

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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. Source: Author's own calculated based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

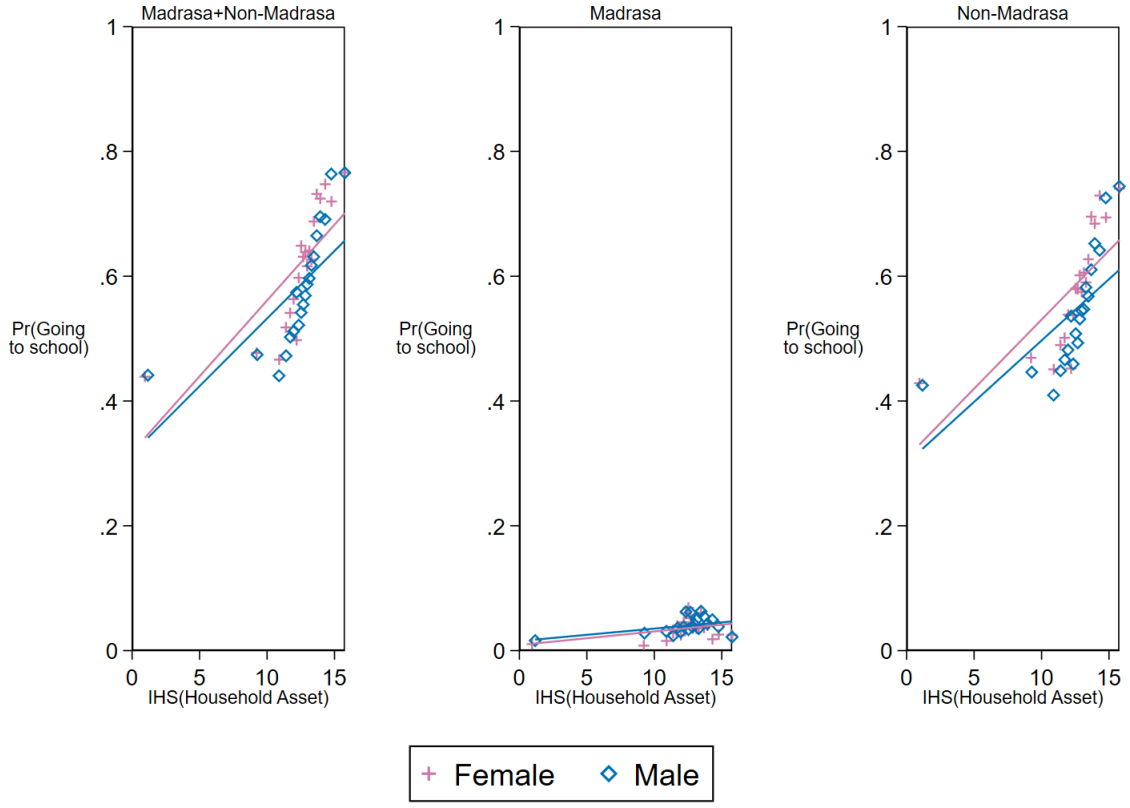
Figures

Figure 1: The Probability of A Child from a Non-migrant Household Attending School in Relation to the Household's Total Income



The figure is showing the relative change in the probability of a child from a non-migrant household to attend any (or a madrasa or a non-madrasa) school with the change in the inverse hyperbolic sine (IHS) transformation of the total income of the household (in Bangladesh Taka). Source: Author's own calculation from the HIES 2010.

Figure 2: The Probability of A Child from a Non-migrant Household Attending School in Relation to the Household's Total Asset



The figure is showing the relative change in the probability of a child from a non-migrant household to attend any (or a madrasa or a non-madrasa) school with the change in the inverse hyperbolic sine (IHS) transformation of the total asset of the household (in Bangladesh Taka). Source: Author's own calculation from the HIES 2010.

Appendix A

Table A1: Descriptive Statistics of Individual- and Household-Level Outcome Variables in the HIES 2016

	Household has			
	A migrant in a Muslim-majority country	A migrant in a non-Muslim-majority country	No migrant abroad	All households
Individual level				
Goes to madrasa				
A child	0.07	0.05	0.05	0.05
A male child	0.08	0.06	0.06	0.06
A female child	0.06	0.04	0.04	0.04
Goes to non-madrasa school				
A child	0.84	0.85	0.83	0.83
A male child	0.82	0.84	0.81	0.81
A female child	0.87	0.86	0.85	0.86
Does not go to school				
A child	0.08	0.09	0.12	0.12
A male child	0.10	0.09	0.13	0.13
A female child	0.07	0.09	0.11	0.11
Total number of children	3,707	863	51,942	56,439
Household level				
Goes to madrasa				
At least one child	0.10	0.07	0.06	0.07
At least one male child	0.06	0.04	0.04	0.05
At least one female child	0.04	0.04	0.03	0.03
Goes to non-madrasa school				
At least one child	0.89	0.93	0.89	0.89
At least one male child	0.57	0.59	0.58	0.58
At least one female child	0.58	0.61	0.57	0.57
Does not go to school				
Any child	0.05	0.05	0.08	0.08
Any male child	0.38	0.38	0.39	0.39
Any female child	0.38	0.37	0.41	0.41
Total number of households	2,114	469	29,654	32,204

Table showing the means of the individual- and household-level outcome variables by migration status of a household and for the total estimation sample of the 2016 round of the HIES. 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. Source: Author's own calculation based on the HIES 2016.

Table A2: Descriptive Statistics of Other Individual- and Household-Level Variables in the HIES 2016

	Household has			
	A migrant in a Muslim-majority country	A migrant in a non-Muslim-majority country	No migrant abroad	All households
Individual level				
Sex of the child (male=1)	0.51	0.49	0.52	0.52
Average age (in years)				
All children	11.58	11.61	11.49	11.50
All male children	11.43	11.72	11.57	11.56
All female children	11.73	11.50	11.40	11.42
Total number of children	3,707	863	51,942	56,439
Household level				
Household head is				
Male	0.46	0.58	0.91	0.87
Muslim	0.96	0.94	0.88	0.88
Household Location				
Metropolitan	0.01	0.02	0.05	0.04
Urban	0.21	0.28	0.25	0.25
Rural	0.78	0.70	0.70	0.70
Household head is				
Male	0.40	0.57	0.92	0.88
Muslim	0.95	0.92	0.87	0.87
Household has				
An adult (>23 years old) who went to madrasa	0.02	0.02	0.02	0.02
A member who returned from abroad during last five years	0.09	0.10	0.03	0.04
Education of household head				
No formal education	0.31	0.31	0.44	0.43
Primary or below	0.26	0.26	0.25	0.25
Secondary	0.39	0.36	0.23	0.24
Post secondary	0.05	0.07	0.08	0.08
Total number of households	2,114	469	29,654	32,204

Table showing the means of the individual- and household-level characteristics by migration status of a household and for the total estimation sample of the 2016 round of the HIES. 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. Source: Author's own calculation based on the HIES 2016.

Table A3: Descriptive Statistics of the Instrumental Variables

	Household has a migrant in a Muslim-majority country		Household has a migrant in a non-Muslim-majority 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
Non-Muslim-majority country	0.02	0.04	0.02	0.08
Total number of households	8,420	758	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. Source: Author's own calculation using the HIES 2010.

Table A4: Individual-Level Effects of a Household Having a Migrant Abroad on the Likelihood of Sending a Child to a Madrasa Conditional on Sending the Child to a School

Dependent variable: Goes to a madrasa Conditional on Attending 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	-0.000	0.089*	-0.002	0.167***	0.002	-0.005
	(0.011)	(0.052)	(0.015)	(0.064)	(0.012)	(0.062)
Non-Muslim-majority country	-0.012	-0.068	-0.020	-0.241	-0.006	0.076
	(0.019)	(0.163)	(0.024)	(0.215)	(0.022)	(0.214)
Sub-district fixed effects	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

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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculation based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: 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) 2SLS	(2) 2SLS
Household has a migrant in a		
Muslim-majority country*Non-Muslim-majority country	1.194	1.903
	(0.944)	(1.675)
Household has a migrant in a		
Muslim-majority country	0.103**	0.121**
	(0.047)	(0.061)
Non-Muslim-majority country	-0.340	-0.383
	(0.307)	(0.439)
Sub-district fixed effects	Yes	Yes
Sample mean	0.04	0.05
N	9,322	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) 2SLS	(2) 2SLS
Household has a migrant in a		
Muslim-majority country*Non-Muslim-majority country	0.787	0.819
	(0.757)	(1.059)
Household has a migrant in a		
Muslim-majority country	-0.005	0.032
	(0.037)	(0.050)
Non-Muslim-majority country	-0.077	-0.127
	(0.171)	(0.347)
Sub-district fixed effects	Yes	Yes
Sample mean	0.04	0.04
N	8,741	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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. Source: Author's own calculation based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: First-Stage Estimates (Using the 2016 Round of the HIES)

	Dependent variable: Household has a migrant in a Muslim-majority country			**Dependent variable: Household has a migrant in a non-Muslim-majority country**		
	Second-stage estimation sample universe:					
	Individual		Household	Individual		Household
	(1)	(2)	(3)	(4)	(5)	(6)
	Male children	Female children	All households	Male children	Female children	All households
The PSU-level leave-on-out fraction of households with a migrant in a						
Muslim-majority country	0.603***	0.643***	0.651***	0.048***	0.026*	0.047***
	(0.025)	(0.025)	(0.017)	(0.014)	(0.015)	(0.010)
Non-Muslim-majority country	0.139**	0.157***	0.184***	0.395***	0.506***	0.409***
	(0.055)	(0.060)	(0.046)	(0.063)	(0.098)	(0.062)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr.	0.10	0.10	0.10	0.04	0.05	0.03
Olea-Pflueger F-statistics	358.11	372.06	774.72	40.86	28.11	52.29
Critical Value for 5% of worst case bias	11.17	6.31	7.35	23.41	32.58	31.46
Critical Value for 10% of worst case bias	7.69	4.85	5.45	14.89	20.27	19.62
N	29,307	27,132	32,204	29,307	27,132	32,204

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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. The Olea-Pflueger F-statistics and 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. Source: Author's own calculation based on the HIES 2016. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Individual-level Effects from Pooling the HIES 2010 and 2016.

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	0.099**	0.044	0.154***
	(0.048)	(0.061)	(0.053)
Non-Muslim-majority country*Survey year=2016	0.125	0.260	0.053
	(0.174)	(0.235)	(0.168)
Household has a migrant in a			
Muslim-majority country	0.055*	0.104**	0.003
	(0.031)	(0.042)	(0.038)
Non-Muslim-majority country	-0.057	-0.176	0.011
	(0.094)	(0.153)	(0.094)
Survey year=2016	0.076***	0.040*	0.114***
	(0.016)	(0.022)	(0.021)
Sub-district fixed effects	Yes	Yes	Yes
N	74,502	38,629	35,873

All regressions include the following control variables: age of the child and square of age, whether any adult above 23 years of age went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, the education of the household head, and all these variables interacted with the survey year dummy. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculation based on the HIES 2010 and 2016. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Individual-level Effect of Household Having A Migrant Abroad on the Schooling Decision of a Child of the Household (Using the 2016 Round of the HIES)

	Panel A			*Panel B*			*Panel C*		
	Dependent variable: Goes to a madrasa			**Dependent variable: Goes to any school**			**Dependent variable: Goes to a non-madrasa school**		
	(1) A child	(2) A male child	(3) A female child	(4) A child	(5) A male child	(6) A female child	(7) A child	(8) A male child	(9) A female child
Household has a migrant in a									
Muslim-majority country	0.154***	0.147***	0.160***	0.045	0.009	0.081**	-0.110**	-0.138**	-0.078
	(0.040)	(0.048)	(0.041)	(0.033)	(0.046)	(0.037)	(0.050)	(0.065)	(0.052)
Non-Muslim-majority country	0.056	0.083	0.041	0.164	0.230	0.095	0.108	0.148	0.054
	(0.153)	(0.189)	(0.145)	(0.129)	(0.180)	(0.115)	(0.198)	(0.263)	(0.171)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.05	0.06	0.04	0.88	0.87	0.89	0.83	0.81	0.86
N	56,439	29,307	27,132	56,439	29,307	27,132	56,439	29,307	27,132

All coefficients are 2SLS estimates. Each regression includes 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculation based on the HIES 2016. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Household-Level Effects of a Household Having a Migrant Abroad on the Schooling Decision of Its Children (Using the 2016 Round of the HIES)

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	0.023***	0.220***	0.018**	0.176***	0.020***	0.177***
	(0.007)	(0.050)	(0.008)	(0.051)	(0.007)	(0.044)
Non-Muslim-majority 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 effects	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) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 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)
Non-Muslim-majority 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 effects	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 a madrasa, whether the household head is a Muslim,whether the household has any member who returned from abroad within the last five years after living there for at least six months, 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. Source: Author's own calculation based on the HIES 2016. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

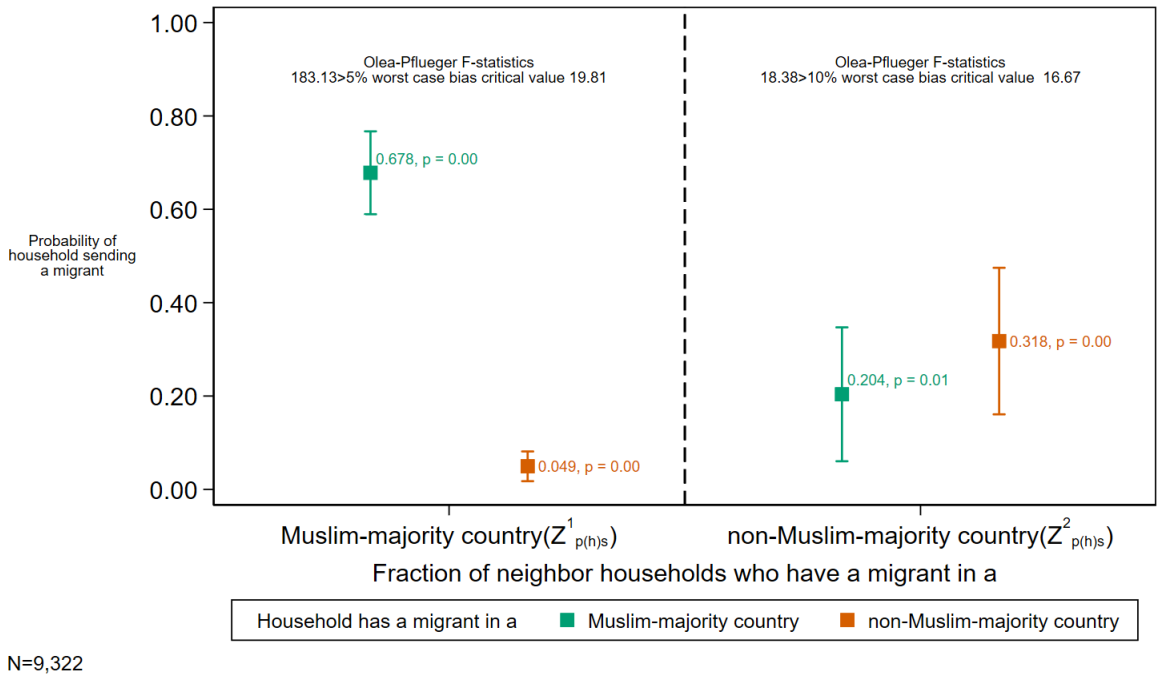
Table A10: Heterogeneous Effects on Madrasa Schooling by Household Income

Panel A: Madrasa schooling of male children												
	Dependent Variable: Goes to a madrasa						Dependent Variable: Goes to a non-madrasa school					
	Age group						Age group					
	5-10	11-18	5-11	12-18	5-12	13-18	5-10	11-18	5-11	12-18	5-12	13-18
Household has a migrant in a												
Muslim-majority country	0.078	0.133**	0.085*	0.135**	0.092*	0.123*	-0.020	-0.206*	-0.163	-0.120	-0.156	-0.095
	(0.070)	(0.060)	(0.049)	(0.064)	(0.054)	(0.063)	(0.202)	(0.115)	(0.141)	(0.119)	(0.136)	(0.116)
Non-Muslim-majority country	-0.129	-0.181	-0.104	-0.198	-0.074	-0.192	-0.526	0.473	-0.083	0.379	-0.100	0.440
	(0.476)	(0.180)	(0.337)	(0.180)	(0.300)	(0.183)	(1.348)	(0.345)	(0.902)	(0.342)	(0.753)	(0.357)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.02	0.06	0.02	0.06	0.03	0.06	0.32	0.74	0.36	0.74	0.41	0.76
N	4,242	5,080	4,832	4,490	5,641	3,681	4,242	5,080	4,832	4,490	5,641	3,681
Panel B: Madrasa schooling of female children												
	Dependent Variable: Goes to a madrasa						Dependent Variable: Goes to a non-madrasa school					
	Age group						Age group					
	5-10	11-18	5-11	12-18	5-12	13-18	5-10	11-18	5-11	12-18	5-12	13-18
Household has a migrant in a												
Muslim-majority country	0.057	-0.034	0.046	-0.046	0.020	-0.028	-0.035	0.120	-0.050	0.162	-0.029	0.192*
	(0.036)	(0.060)	(0.044)	(0.063)	(0.041)	(0.065)	(0.168)	(0.106)	(0.177)	(0.103)	(0.159)	(0.105)
Non-Muslim-majority country	-0.128	0.038	-0.026	0.006	0.037	-0.049	0.084	-0.359	0.038	-0.362	-0.222	-0.213
	(0.099)	(0.166)	(0.221)	(0.155)	(0.179)	(0.153)	(0.628)	(0.324)	(0.741)	(0.263)	(0.689)	(0.263)
Sub-district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	0.01	0.06	0.02	0.06	0.02	0.06	0.35	0.79	0.40	0.80	0.44	0.82
N	4,095	4,646	4,694	4,047	5,424	3,317	4,095	4,646	4,694	4,047	5,424	3,317

All regressions include the following control variables: age of the child and square of age, whether any adult above 23 years of age went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, the education of the household head, and all these variables interacted with survey year dummy. Standard errors, clustered at PSU, in parentheses. Source: Author's own calculation based on the HIES 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

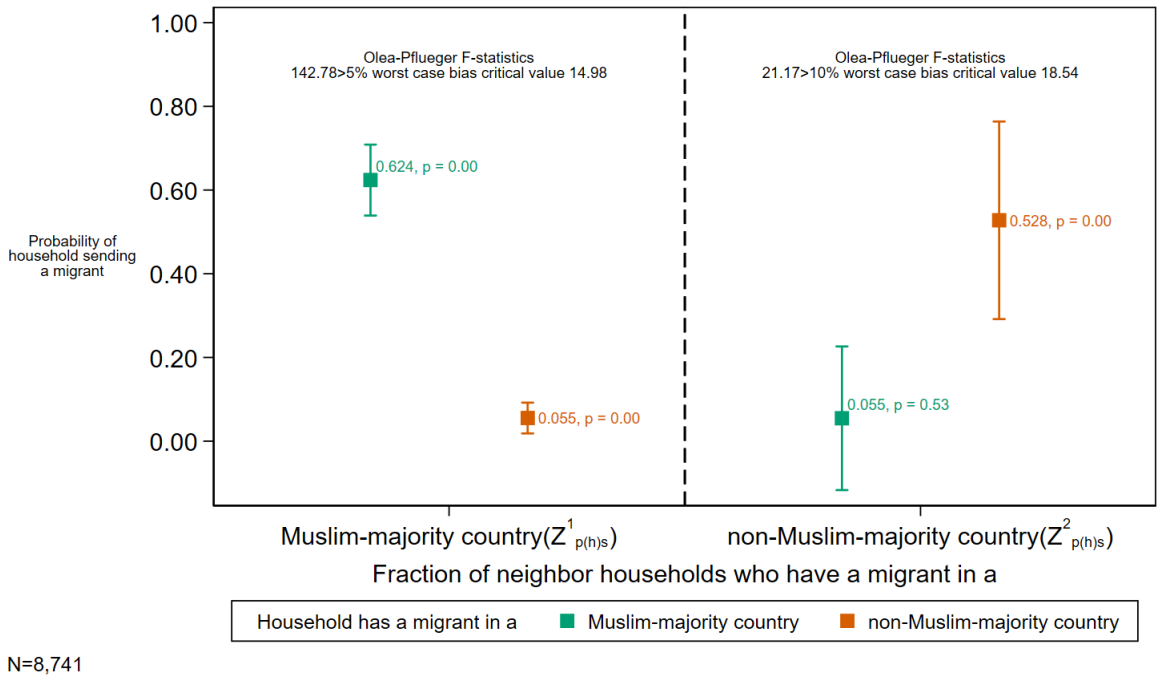
Appendix B

Figure B1: First-stage Estimates for Individual-Level Specification at the Second Stage (Male Children Only)



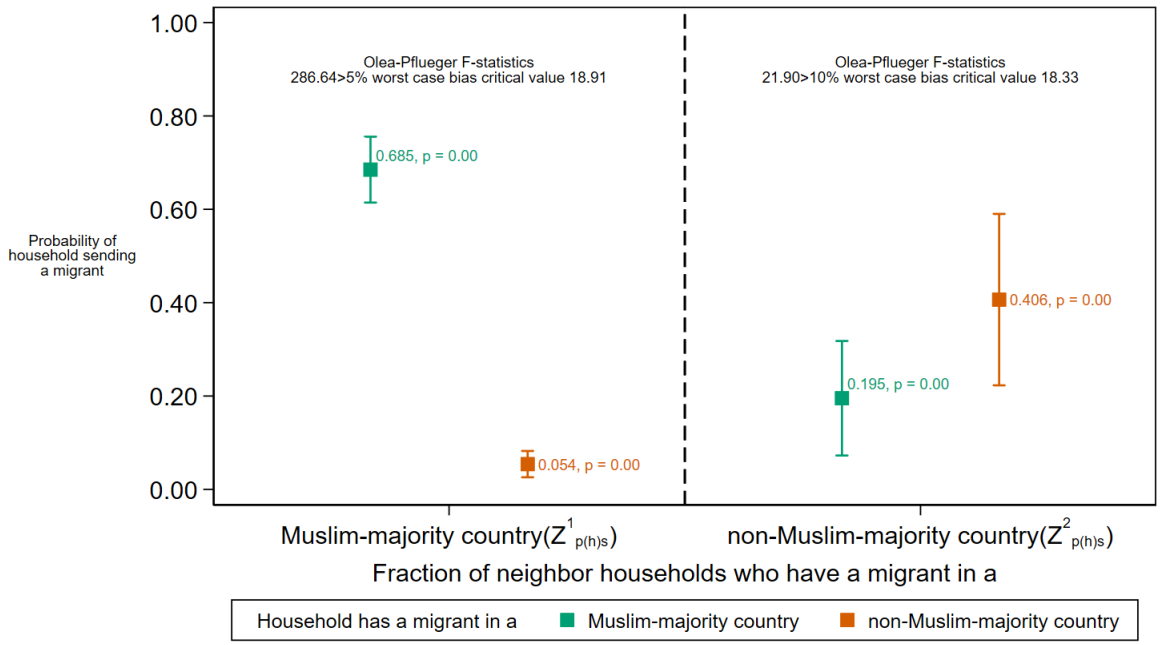
The figure is showing the first-stage estimates for the individual-level specification. The second-stage sample is restricted to male children of 5-18 years of age. All regressions include the following control variables: sub-district fixed effects, age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

Figure B2: First-stage Estimates for Individual-Level Specification at the Second Stage (Female Children Only)



The figure is showing the first-stage estimates for the individual-level specification. The second-stage sample is restricted to male children of 5-18 years of age. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

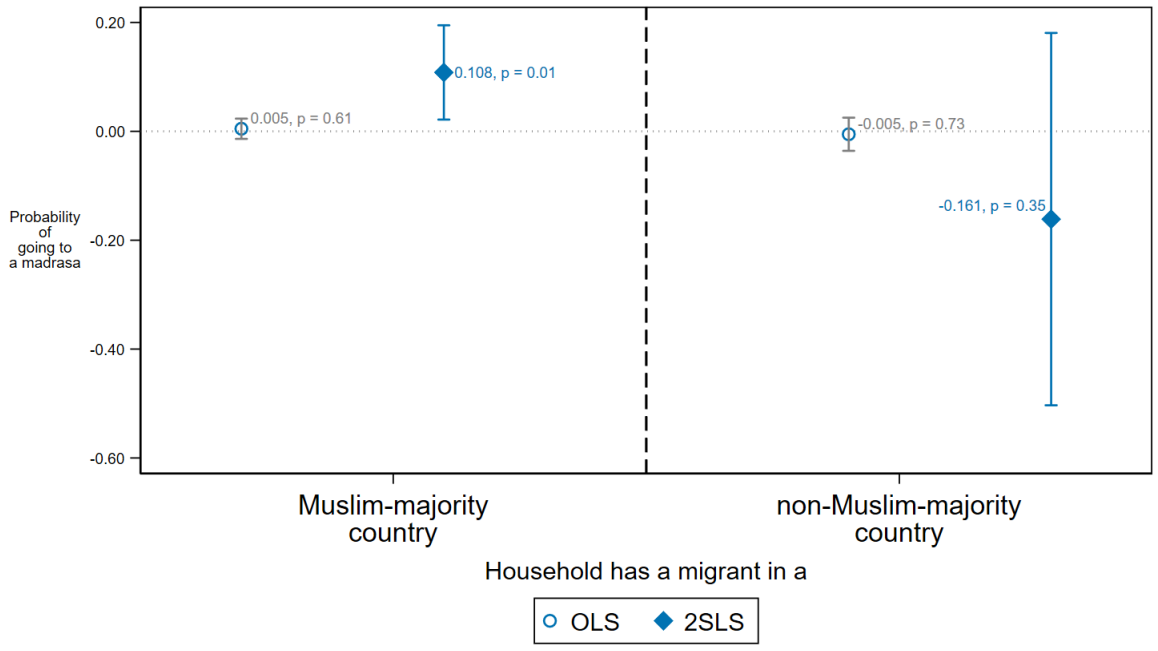
Figure B3: First-stage Estimates for Household-Level Specification at the Second Stage



N=9,178

The figure is showing the first-stage estimates for the household-level specification. The second-stage sample is restricted to all households who have at least one child of 5-18 years of age. All regressions include the following control variables: sub-district fixed effects, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

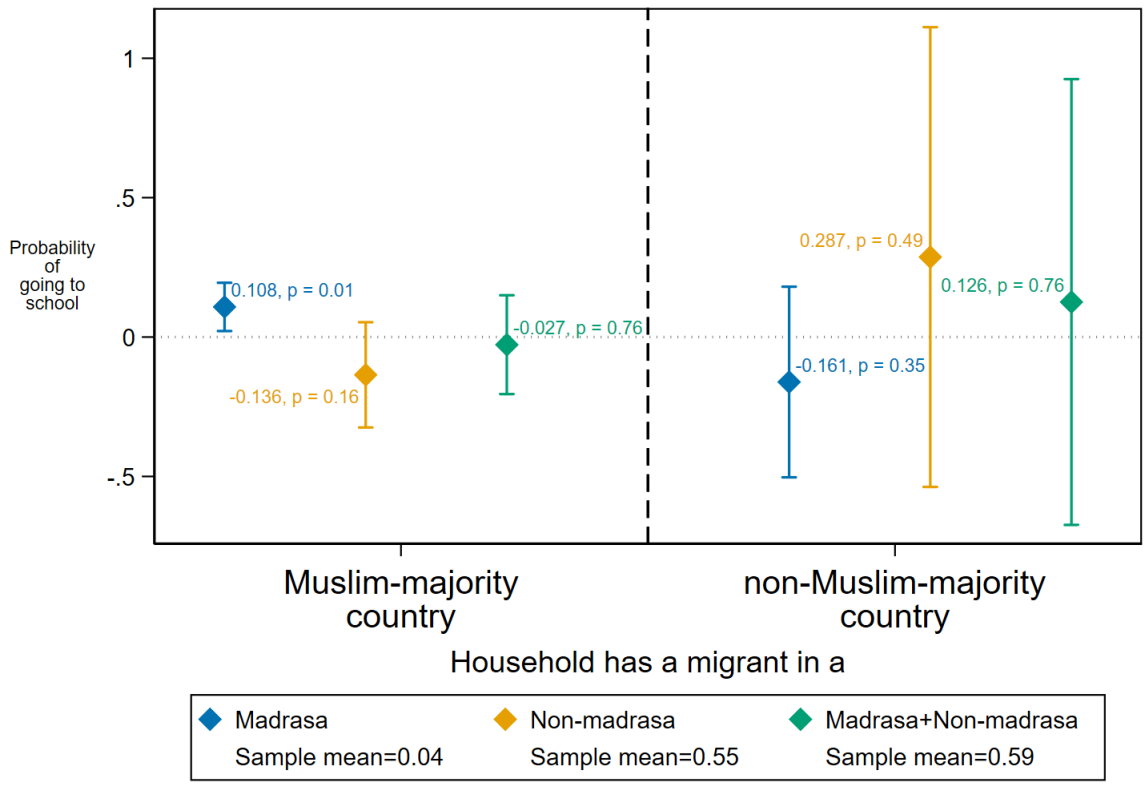
Figure B4: Individual-Level Effects of a Household Having a Migrant Abroad on the Likelihood of Sending a Male Child to a Madrasa



All regressions are restricted to male children of 5-18 years of age. Sample mean=0.04, N=9,322

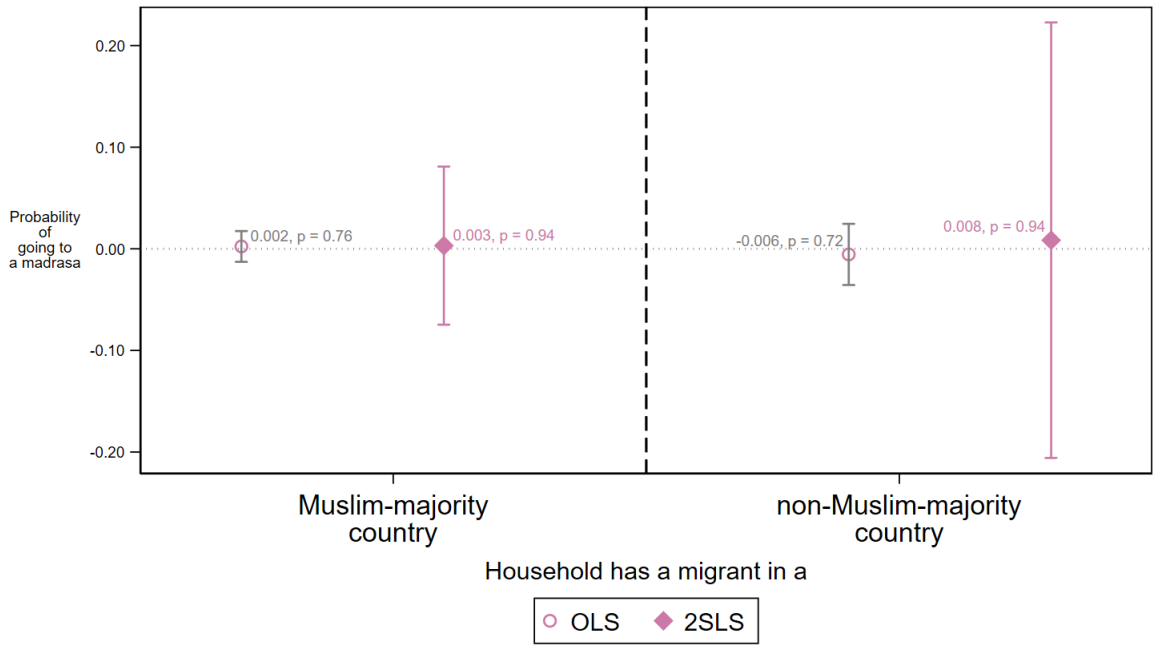
The figure is showing the effects of a household sending a migrant abroad on the likelihood of sending a male child to a madrasa. All regressions include the following control variables: sub-district fixed effects, age of the child and square of age, whether the household has an adult aged 23 years or older who went to a madrasa, whether the household head is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

Figure B5: Individual-Level Effects of a Household Having a Migrant Abroad on the Schooling Decision of a Male Child



The figure is showing the effects of a household sending a migrant abroad on the schooling decision of a male child of the household. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

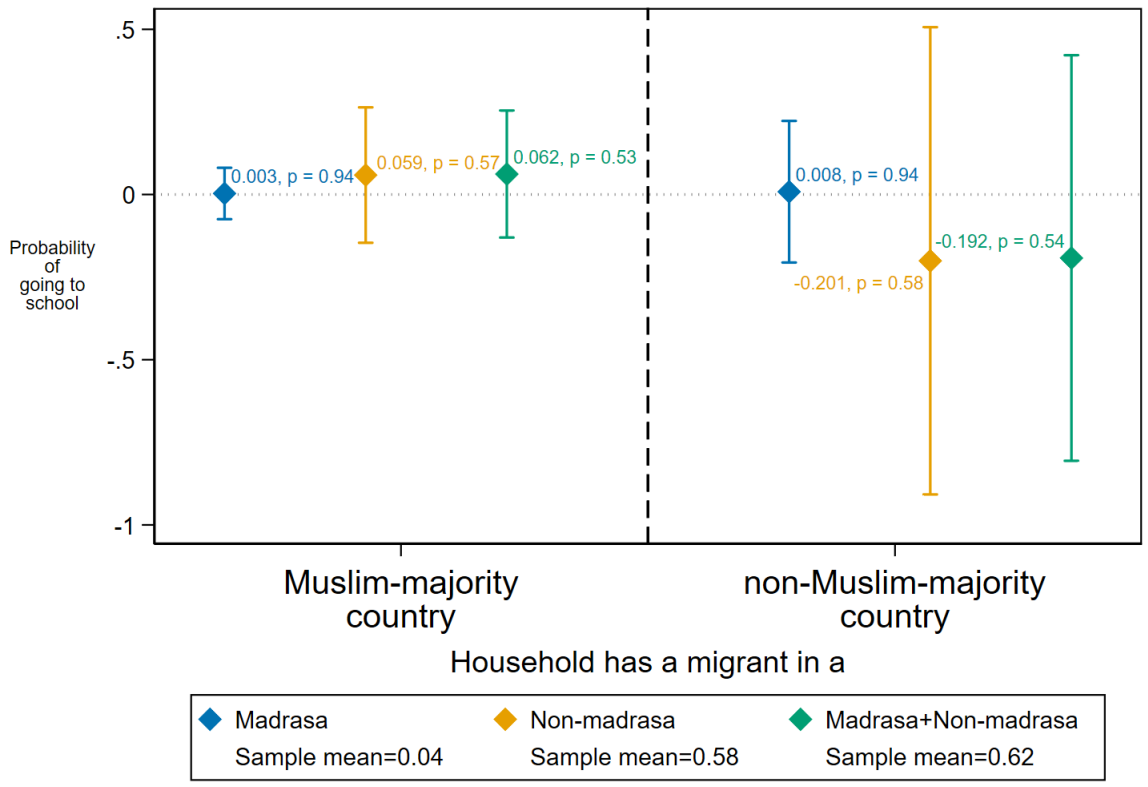
Figure B6: Individual-Level Effects of a Household Having a Migrant Abroad on the Likelihood of Sending a Female Child to a Madrasa



All regressions are restricted to female children of 5-18 years of age. Sample mean=0.04, N=8,741

The figure is showing the effects of a household sending a migrant abroad on the likelihood of sending a female child to a madrasa. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

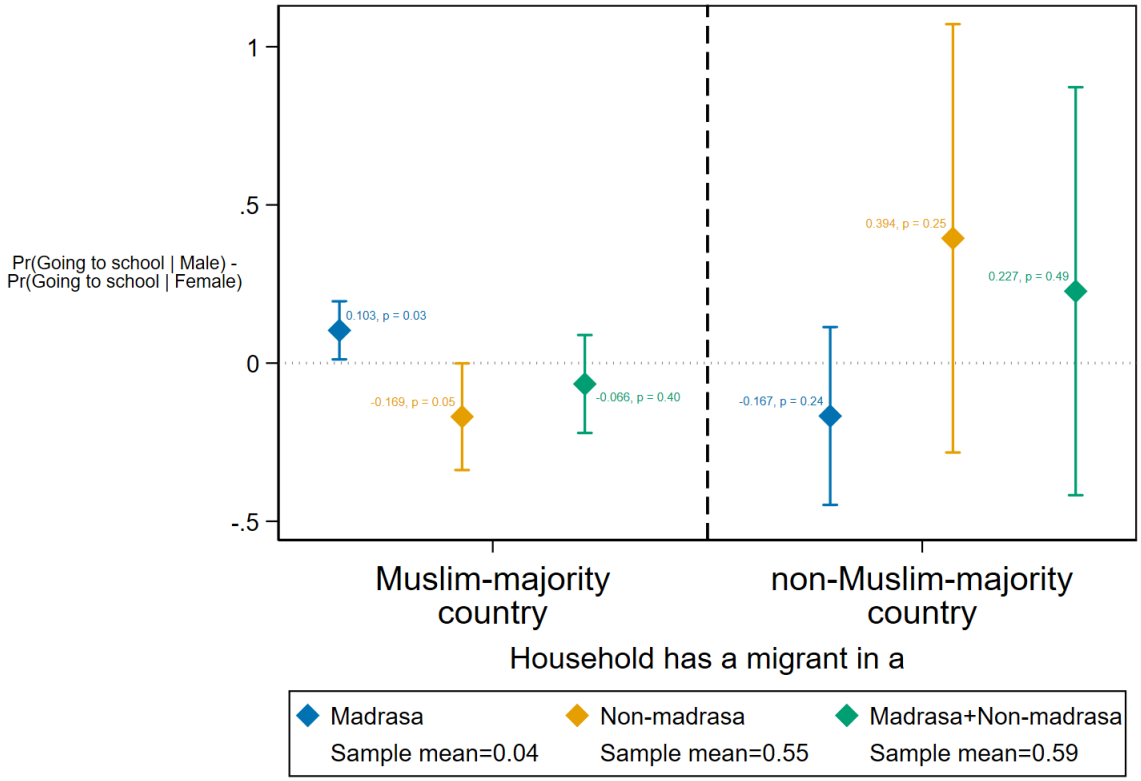
Figure B7: Individual-Level Effects of a Household Having a Migrant Abroad on the Schooling Decision of a Female Child



All regressions are restricted to female children of 5-18 years of age. N=8,741

The figure is showing the effects of a household sending a migrant abroad on the schooling decision of a female child of the household. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

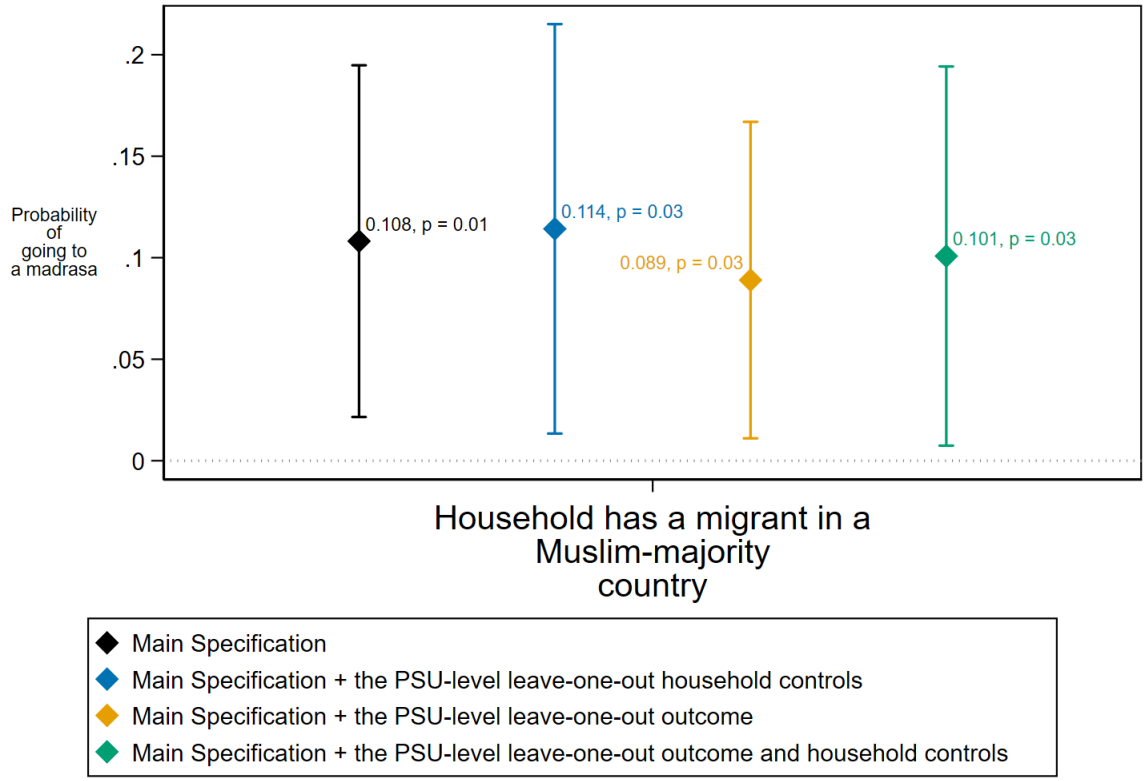
Figure B8: Difference of Individual-Level Effects by the Sex of the Child



All regressions are restricted to children of 5-18 years of age. N=18,063

The figure is showing the difference between the effects of a household sending a migrant abroad on the schooling decision of a male child and a female child. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

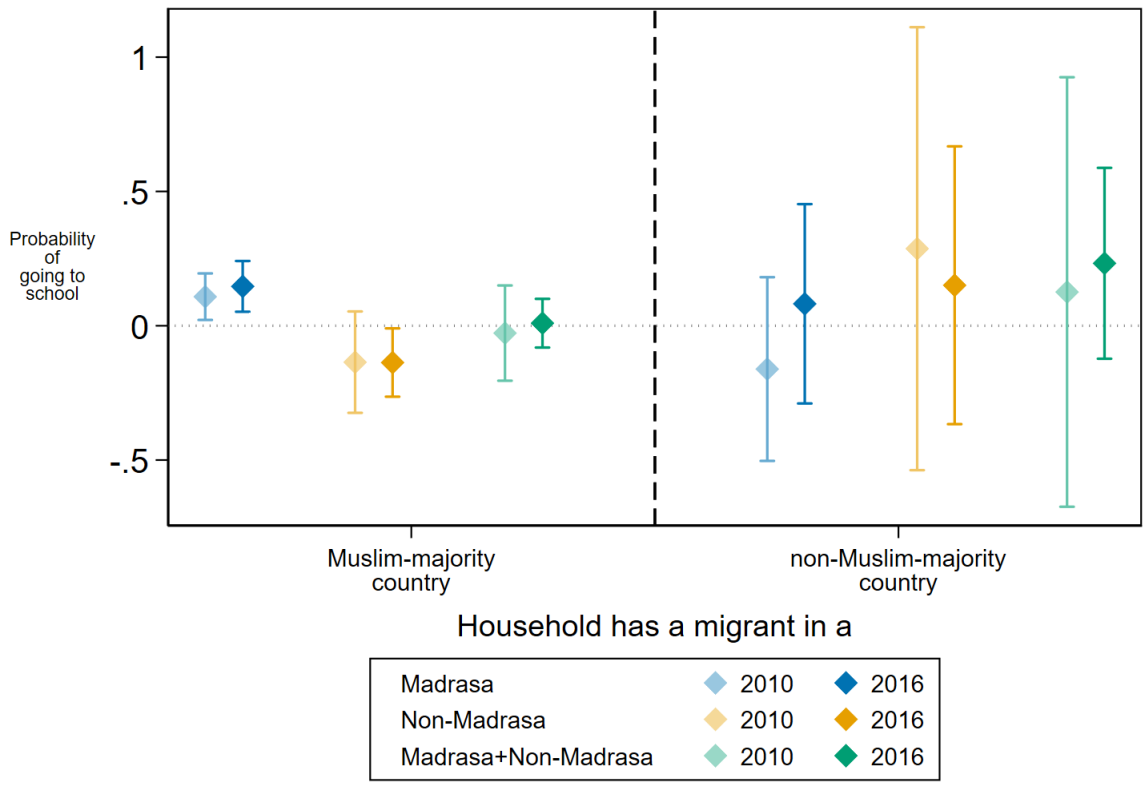
Figure B9: Tests on Neighbor Characteristics Influencing Madrasa Schooling



All regressions are restricted to male children of 5-18 years of age. Sample mean=0.04, N=9,322

The figure is showing whether the individual-level effects of a household sending a migrant abroad on the likelihood of sending a male child to a madrasa changes when the PSU-level leave-one-out outcome and household controls are included. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010.

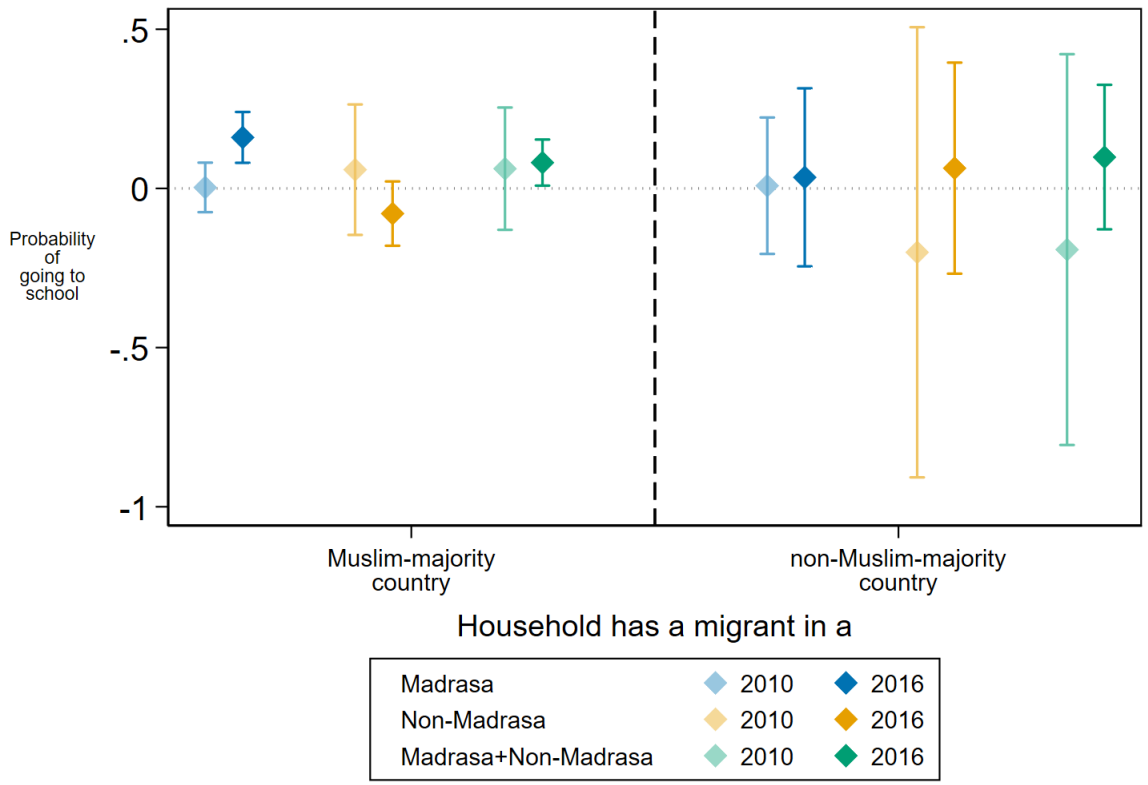
Figure B10: Comparison between the HIES 2010 and HIES 2016 Estimates of Individual-Level Effects on the Schooling of Male Children



All regressions are restricted to male children of 5-18 years of age.

The figure is showing a comparison between the HIES 2010 and HIES 2016 estimates of the effects of a household sending a migrant abroad on the schooling decision of a male child. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010 and 2016.

Figure B11: Comparison between the HIES 2010 and HIES 2016 Estimates of Individual-Level Effects on the Schooling of Female Children



All regressions are restricted to female children of 5-18 years of age.

The figure is showing a comparison between the HIES 2010 and HIES 2016 estimates of the effects of a household sending a migrant abroad on the schooling decision of a female child. All coefficients are 2SLS estimates. All regressions include the following control variables: sub-district fixed effects, 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 is a Muslim, whether the household has any member who returned from abroad within the last five years after living there for at least six months, and dummy variables for the level of education of the household head. Standard errors are clustered at PSU. Source: Author's own calculation based on the HIES 2010 and 2016.

Appendix C

Equations for Household-Level Analysis

The first-stage regressions:

$$M^1_{hps} = \sigma_s + \sigma_1 Z^1_{p_{(h)}s} + \sigma_2 Z^2_{p_{(h)}s} + \sigma_3 H_{hps} + \phi_{hps} \tag{C1}$$

$$M^2_{hps} = \tau_s + \tau_1 Z^1_{p_{(h)}s} + \tau_2 Z^2_{p_{(h)}s} + \tau_3 H_{hps} + \kappa_{hps} \tag{C2}$$

The second stage is:

$$Y_{hps} = \pi_s + \pi_1 \widehat{M^1}_{hps} + \pi_2 \widehat{M^2}_{hps} + \pi_3 H_{hps} + \omega_{hps} \tag{C3}$$

Here, π_1 and π_2 from a two-staged least squares estimation are consistent estimators of interest.

Exclusion Bias

Table C1: 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

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 a negative bias (Guryan et al., 2009).