The impact of return migration on the school–work tradeoff and labor outcomes of adolescents*

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Abstract

Return migration is an intrinsic part of the cycle of international migration and development. In this study, I examine the causal effect of return migration on the *school–work tradeoff* and *selection into employment types* of children aged 12–19 years in Mexican households. I use the Mexican census of 2010 and various other sources to construct a unique dataset. I employ the control function approach and use U.S. state-level immigration enforcement acting as push factors as an instrument to address the endogeneity of return migration. My results suggest an increase in the probability of school attendance, a decrease in labor market participation, and a decrease in the probability of working and going to school simultaneously for children of households with return migrants, relative to non-migrant households. Moreover, I find a decrease in the probability of employment in wage/salaried work, and an increase in self-employment among children in return migrant households. I speculate that these improvements are driven by the migrants' experience, accumulation of human and financial capital in the United States, as well as better labor market opportunities when they return. This paper suggests return migration from a developed to a developing country as a mechanism through which migrant flows may benefit origin developing countries worldwide. Policies aimed at assisting the reintegration of return migrants in local markets may substantially improve the quality of education and can act as a channel to reduce child labor.

Keywords: Return Migration, Education, Child Labor, Mexico
JEL Classification: F22, O15, J81

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1 Introduction

Return migration is an intrinsic part of the cycle of international migration and development. Although there is growing attention toward border protection in recent years, there is sparse research on understanding the impact of return migration on the origin country. The U.S.–Mexico corridor represents one of the most massive migrant movements in human history. Since 2007 the trend has reversed, with more Mexican migrants returning to their homes than those moving to the United States (Figure 1). 1.39 million people moved to Mexico from the U.S. between 2005 and 2010, many of whom were Mexican-born return migrants who lived in the U.S. at some point but returned to Mexico. This is a four-fold[1] increase in the number of return migrants compared to 2000 (Hazán, 2017). While a small percentage were deported, the majority returned voluntarily (Gonzalez-Barrera, 2015; Passel, Cohn, & Gonzalez-Barrera, 2012).

For many developing countries, the migration of their highly skilled workforce is a cause of concern. However, although migration may lead to short-term brain drain, there can be potential brain gain with return migration (Docquier & Rapoport, 2012; Wahba & Zenou, 2012). The experiences gained abroad benefit not just the return migrants but may also cause spillover effects that enhance their households' living and economic conditions. In this study, I examine the causal effect of a return migrant in the household on the children's school–work tradeoff and occupation choices. The return of the migrants with their accumulated experiences, skills, and financial stability (Cassarino, 2004; Dustmann & Kirchkamp, 2002; King & Levine, 1993) can contribute to the overall development of children in the households through more investment in education and knowledge diffusion (Dos Santos & Postel-Vinay, 2003; Dustmann & Görlach, 2016; Mayr & Peri, 2009; Sun, 2013). Moreover, I examine whether return leads to a decrease in children's workload and unpaid activities, further assessing the role of a return migrant household in their children's occupational decisions and, consequently, their well-being.

In households where either the parent or the head of the household migrates, leaving

[1]Return migration to Mexico of Mexicans living in the United States five years before the Mexican 2010 census was 985,000, while the corresponding number in 2000 census was 280,000.

the family behind, the older child mostly takes the responsibility to fill the void of the migrant in these households care. In most cases, the household has to support the migrant (Gibson, McKenzie, & Stillman, 2011) and often provide for them financially, as the initial years of migration may be tough due to the difficulty in finding work. Moreover, for low-income families dealing with extreme poverty, investing in education is a type of financial burden. Therefore, children are forced to drop out of school and engage in income-earning activities even if their parents prefer education (Baland & Robinson, 2000; Basu & Van, 1998; Beegle, Dehejia, & Gatti, 2009; Edmonds, 2006; Ranjan, 2001). Even when they do not drop out, they may work and go to school simultaneously to help provide the basic necessities for their families.

Income uncertainty is a ubiquitous feature of life for those living in poverty, which is likely to be alleviated rather than exacerbated when there is a return migrant in the household. Return migrants acquire new skills and accumulate human capital and savings during their stay in the host country. When they return, the increased probability of upward occupational mobility (El-Mallakh & Wahba, 2021), wage increase (Campos-Vazquez & Lara, 2012; Lacuesta, 2010; Reinhold & Thom, 2013; Wahba, 2015; Wahba & Zenou, 2012), and savings invested in entrepreneur activities (Batista, Mcindoe-Calder, & Vicente, 2017; Dustmann & Kirchkamp, 2002; Wahba & Zenou, 2012) may relax income constraints and improve the human capital outcomes of children in the household.

To conduct the empirical analysis, I use the 2010 Population and Housing Census of Mexico. Specifically, I explore the effect of temporary migration experiences on the human capital and labor outcomes of adolescents. I compare children aged 12–19 in households with migration experiences from the United States to those of non-migrant households. The main variable of interest, *households with return migrants*, is potentially endogenous. There may be unobserved determinants of the children's school–work decisions and labor choices correlated with the household's return migration status, such as sudden mishaps in the family or households preference towards education. Consequently, to identify the causal effect of return migration on children's occupational decisions, I use the control function approach. 91% of Mexican who migrate, migrate to the USA.[2] Therefore, any changes to U.S. immigration enforcement serve as push factors inducing an increase in the probability of return migration to the home country. I use the exposure of Mexican municipalities to *U.S. immigration enforcement exposure* as an instrument for return migration in households.

The results indicate that adolescents in households with return migrants are more likely to attend school and less likely to work compared to non-migrant households. Moreover, concerning the selection into employment types, adolescent children in return migrant households are more likely to be self-employed and less likely to be wage or salaried workers or engage in unpaid activities. This indicates the better quality of jobs that adolescents in return migrants select into since most of the wage/salaried work is likely to be low-paying as well as poor quality. I also explore the heterogeneity of the effects across gender, age, and household wealth.

The research contributes to two main strands of literature. First, it builds on a growing body of literature focused on the link between return migration and economic prosperity in the country of origin. Return migrants benefit from their overseas tenure across various dimensions, mainly in terms of labor and social outcomes. In the hometown communities and regions, return migration strengthens political rights (Barsbai, Rapoport, Steinmayr, & Trebesch, 2017; Batista & Vicente, 2011; Mercier, 2016; Perez-Armendariz & Crow, 2010; Spilimbergo, 2009), reduces crime (Bucheli, Fontenla, & Waddell, 2019), brings back new methods and technologies to increase productivity (Bahar, Özgüel, Hauptmann, & Rapoport, 2019) and investment (Marchetta, 2012; Wahba & Zenou, 2012), and contributes to economic development (Bucheli et al., 2019). At the individual level, return migrants perform better in the labor market and are influenced by the host country's social norms (Dustmann & Görlach, 2016; Wahba, 2014), earn higher wages relative to non-migrant households (Campos-Vazquez & Lara, 2012; Lacuesta, 2010; Reinhold & Thom, 2013; Wahba, 2015; Wahba & Zenou, 2012) and start entrepreneurial activities (Batista et al., 2017; Dustmann & Kirchkamp, 2002; Wahba & Zenou, 2012) whose

[2] Authors calculation from 2010 census.

survival rates also increase (Marchetta, 2012). Second, it contributes to the extensive literature that examines the tradeoffs between child labor and schooling (Beegle et al., 2009; Emerson, Ponczek, & Souza, 2014; Putnick & Bornstein, 2015; Ray & Lancaster, 2005). My results provide suggestive evidence of how the effect of international migration experiences, driven by the transmission of accumulated human, financial, and social capital, may contribute to improved labor outcomes of adolescents.

2 Background

A migrant decides to migrate weighing the costs and benefits of relocating (Borjas, 2001). Similarly, a return migrant considers the cost and benefit of moving back to their home country. In line with the life-cycle behavior, Yang (2008) finds that positive exchange rate shocks decrease return migration as the incentive of staying increases. Moreover, McKenzie, Theoharides, and Yang (2014) find that an increase in economic growth in the destination country positively affects migration decisions. Several factors have attributed to the reverse trend for the U.S.–Mexico corridor. The Great Recession of 2007–2009 led to fewer employment opportunities for migrants (Villarreal & Hamilton, 2012), costly and dangerous crossings (Gathmann, 2008; Massey, Durand, & Pren, 2014), increasing border enforcement, and discrimination against Mexicans living in the United States (Fernández-Kelly & Massey, 2007). Other reasons for return migration consist of anti-immigrant attitudes in the host country (de Coulon, Radu, & Steinhardt, 2016), homesickness (Chakraborty & Mandal, 2016), deportation (Gonzalez-Barrera, 2015), and unemployment (Bijwaard, Schluter, & Wahba, 2014).

Although studies document that migration and remittances improve educational outcomes in origin countries (Edwards & Ureta, 2003; Theoharides, 2018; Yang, 2008), parental absence associated with migration may decrease children's educational attainment (McKenzie & Rapoport, 2011). In Mexico, increasing evidence suggests that migration causes a temporary detachment of the migrant from their families (Reyes, 1997). During the initial years of migration of the family member, there may be situations in which the family left behind helps the migrant rather than the other way around (Antman, 2011). The migrant also leaves a void in the family, often forcing the elder child to support the family during those times and increasing the need for children to fill in for the migrant's job. The child in the household might have to drop out of school to work, or perform both activities (McKenzie & Rapoport, 2011). This is more so for adolescent girls in the household when they are assigned to take care of their younger siblings. Furthermore, these decisions are particularly difficult for girls because they are influenced by social norms (Herrera, Sahn, & Villa, 2019). These choices are often made at a young age before being aware of the returns to education.

A household decides to send a child to work if child labor is a critical tool to meet basic needs (Basu & Van, 1998). Lower-income parents often use child labor to have a higher current income; they decide how much time a child spends on leisure, school or work, and doing household work. However, the cost of child labor is not fully internalized by the parents (Edmonds, 2007). Child labor impedes physical and mental development and causes a decrease in human capital accumulation, and hazardous work is associated with harmful effects on children's health.[3] Moreover, working may lower a child's current and future utility and reduce the child's future income.

When migrants return, they bring back knowledge, cultural traits, savings, and experiences accumulated abroad. This may improve the well-being of their children when they choose to resettle in their households as parents and extended family influence decisions about children's time allocation (Edmonds, 2006). In this context, I am interested in estimating the causal effect of a return migrant in the household on the school–work balance and the type of work that adolescents perform. In the U.S.–Mexico scenario, I consider diverse channels through which having a return migrant in the household influences school–work decisions and children's selection into employment types. First, with more savings, the liquidity constraint in these households is eased and they can start their own family business with the financial capital acquired abroad (Ahlburg & Brown,

[3] For instance, exposure to direct sunlight or weather; recurrent injuries at work; danger from animals, insects, and parasites;, and exposure to harmful chemicals may have significant health consequences that only arise after a long period. Ashagrie et al. (2002) find the injury rate for children in agriculture to be 12 percent.

1998; Thomas, 2008). Second, an increase in income resulting from an increase in wages of returnees (Campos-Vazquez & Lara, 2012; Lacuesta, 2010; Reinhold & Thom, 2013; Wahba, 2015; Wahba & Zenou, 2012) can reduce child labor and increase schooling (Baland & Robinson, 2000; Basu & Van, 1998; Edmonds, 2005, 2006). Third, non-pecuniary channels, such as social norms, may also change concerning the treatment of child in a household. Boys are not enrolled in school in underdeveloped nations owing to a lack of parental desire in educating their children. (The Public Report on Basic Education, 1999). Children often accompany their mothers to work and engage in labor because of the lack of another caregiver at home. Such practices in some cases may not be considered deleterious to children's well-being by parents due to cultural norms. These attitudes toward work and schooling may change with new social norms gathered by the return migrant during their stay abroad. Fourth, an increase in parental involvement is needed for a child to prosper (Duflo, Dupas, & Kremer, 2007; Gertler, Patrinos, & Rubio-Codina, 2012; Pandey, Goyal, & Sundararaman, 2009). The void in the family is filled when the migrant returns to the household, bringing back stability. Fifth, working abroad may enable migrants to acquire new skills and accumulate human capital (Beine, Docquier, & Oden-Defoort, 2011; Beine, Docquier, & Rapoport, 2008).[4] There is an increased probability of upward occupational mobility for returnees (Carletto & Kilic, 2011; El-Mallakh & Wahba, 2021), which may positively impact children's schooling decisions and selection into employment types. Sixth, return migrants, with their experiences abroad, have information regarding the returns to education or wage premiums.[5] The migrant returning is likely to motivate the adolescent to continue education and delay labor market entry.

3 Data

To conduct the empirical analysis, I use data from the 2010 Population and Housing Census of Mexico collected by the *Instituto Nacional de Estadistica Geografia e Informatica*

[4]For details, see Dustmann, Fadlon, and Weiss (2011); Mayr and Peri (2009)

[5]For details see Batista, Lacuesta, and Vicente (2012); Beine et al. (2008); Chand and Clemens (2008); Shrestha (2017)

(INEGI) and accessible from the IPUMS-International database (IPUMS, 2020). The 2010 Mexican census used a one-stage stratified cluster sample by municipality. It is one of the few nationally representative samples, containing 11 million individuals from 2.9 million households residing in 2443 Mexican municipalities (roughly equivalent to U.S. counties).[6] Population and housing censuses are the most reliable source of statistical information and allow us to identify socio-economic inequity, disadvantaged groups, and the population's needs in housing, education, health, clean drinking water, electricity, and sanitation. These data are well suited for this paper since they provide detailed statistics on the population's geographic and socio-economic profile allowing us to see the retrospective migration information at individual and household levels.

To construct the instrumental variable and municipality-level control variables, I use various other data sources that I explain in Table A.1 (Appendix). The Mexican census includes person and household weights that account for non-responses and represent the total population.[7]

I focus my analysis on Mexican-born children aged 12–19 years who never migrated to a foreign country. Children who come back from foreign countries might face issues returning to school and therefore choose work because of improper documentation, differing school curricula that do not seamlessly transfer, or language barriers. On the other hand, these children might have had better opportunities and education in a foreign country. Thus, including only children who were always in Mexico helps us avoid the bias arising due to the presence of foreign-born children.

The main variable of interest is a binary variable indicating whether the child lives in a household with a return migrant from the United States. I define households with return migrants as those households where there is at least one individual who lived in

[6] I used full census data available from the IPUMS to extract comprehensible information from the complete population. The entire sample census can have data for small areas and sub-populations to allow detailed cross-tabulations. We can also say the estimates are not subject to sampling error.

[7] Since this is a one-stage stratified sample selection, response rates and coverage rates may vary across sub-populations, and responding units may not be representative of the population. The use of weights in the study offsets this differential representation and generates estimates representative of the target population.

the United States[8] before 2005 and was back in the household after 2005 but before the 2010 census.[9] The control group comprises non-migrant households in which none of the household members migrated or returned during 2005–2010. Additionally, in these households, there are no migrants in the last five years before the census (2005–2010).

The interest lies in measuring the effect of having a return migrant in the household on a child's school–work tradeoff and the type of employment in which the children in these households engage. To estimate the school–work tradeoff for children, I make use of two variables: *employment status*, i.e., whether the adolescent is currently working, and *school attendance*, i.e., whether the adolescent is currently attending school. Based on these variables, children can be segregated into four categories: *School only*, *Work Only*, *Neither*, and *Work & School*. I classify a child as *neither* or *idle* if they report that they are neither working nor going to school.[10] Second, I split the *occupation choices* into four distinct categories: *Non-Participants, Self-Employed, Wage or Salaried worker, and Unpaid Worker*. To check the sensitivity of the results concerning how I define *school–work tradeoff* and *selection into employment types*, I also consider several alternative definitions of the dependent variables explained in Section 6 (Robustness checks).

Figure 2a shows the proportion of children only attending school, only working, neither, and both across age and household return migration status. As expected, the proportion of those only attending school decreases with age and those only working increases with age. The proportion of adolescents neither working nor attending school is highest at age 19, which indicates job search and transition from school to work. I also observe differences across household return migration status, with differences increasing with age. Figure 2b presents the proportions for employment types. Of those who are engaged in economic activity, the largest proportion is those with wage/salaried jobs.

[8]Excluding households with return migrants from any other country ensures the exclusion of the heterogeneous impact of those countries on the return migrants and their decisions.

[9]These return migrants are mostly permanent return migrants who have fulfilled their target for migration and most likely will not migrate again.

[10]There is considerable literature on "idle" children and how the exact interpretation of their status can be controversial. Biggeri, Guarcello, Lyon, Rosati, et al. (2003) argue that measurement errors of domestic work, unemployment, and unobserved health issues can lead to more idle children in the data. Also, see Bacolod and Ranjan (2008); Edmonds (2005); Edmonds, Pavcnik, and Topalova (2010) for more literature on idle children.

Self-employed adolescents are the smallest proportion of those working up to age 16. Larger differences between households with return migrants and non-migrant households emerge in those above 14 years of age.

I create a wealth index[11] (Sahn & Stifel, 2003) to describe the variation in wealth across households using principal component analysis (PCA). I use the first component as a measure of the wealth status of the households. Additionally, I also control for individual, mothers, household, and municipality-level characteristics along with urban and region fixed effects.

Table A.2 reports the descriptive statistics of the full sample. The means for households with only non-migrants and households with only return migrants are reported in Table 1. In Panel A, I report the means of the dependent variables, while in Panel B, I report the means of the control variables included in the regressions. From Panel A in Table 1, we observe that adolescent children in return migrant households work more as wage/salaried or unpaid workers and are less likely to participate in the labor market. On average, adolescents in return migrant households are more likely to be idle, less likely to go to school, more likely to go to work, and more likely to do both than adolescents in non-migrant households, with statistically significant differences. Mothers in return migrant households work fewer hours and are less likely to have completed secondary and higher education. Approximately 60% of mothers are likely to have completed primary education against 54% in non-migrant households. I also find a lower incidence of urban residency for return migrant households, approximately 16 percentage points lower than non-migrant households. Overall, we observe systematic differences between return migrant and non-migrant households in terms of socio-economic characteristics. These averages across the treatment status indicate the presence of negative selection into return migration.[12] Hence, a naive comparison of children's occupational outcomes

[11]The assets that are included are ownership of an automobile, bathing facility, number of bedrooms, phone, computer, electricity, type of floor (unfinished vs. cement and other types of floor), cooking fuel, hot water, internet, kitchen, house, refrigerator, type of roof, sewage (none, private sewage, and public sewage), water supply (not-piped vs. piped water), toilet (none, have toilet, flush toilet), and television.

[12]This pattern is similar to findings in the literature, especially from Mexico (Bucheli et al., 2019). Campos-Vazquez and Lara (2012) and Reinhold and Thom (2013) find negative selection for return migrants compared to non-migrants, but Biavaschi (2016) finds negative selection compared to migrants.

with the return migrant status of the household yields biased estimates.

4 Methodology

Examining the relationship between return migration in a household and the school–work choices of children in those households is not straightforward, as having a return migrant in a household is potentially endogenous. A simple comparison of the means across treatment and control groups provides evidence of selection into return migrant households, making estimating unbiased treatment effects a challenge. I am particularly concerned about reverse causality, for example, if the individual had returned to a household with poor economic status and schooling outcomes.

Therefore, to identify the causal effect of return migration on children's *school–work status* and their *selection into employment types*, I employ a control function approach. The method is an instrumental variable approach, in which the residuals from the first stage are controlled for in the second-stage equation. Using the two-stage least squares (2SLS) approach in a non-linear setting produces inconsistent estimators of parameters and partial effects (Wooldridge, 2015). Employing a control function approach solves this problem and yields consistent estimates (Terza, Basu, & Rathouz, 2008). I use the exposure of Mexican municipalities to interior immigration enforcement in the United States as the source of exogenous variation in the endogenous treatment variable of interest, return migration.[13] The intuition for my choice of instrument is that exposure to higher immigration enforcement in the United States will serves as a push factor inducing an increase in the probability of return migration to the home country. Thus, the instrument affects the school–work choices of adolescents through the presence of a return migrant in the household, rather than by affecting the outcomes directly.

[13] I follow Bucheli and Fontenla (2019), who, in their study of the impact of return migration on development in Mexican municipalities, use economic conditions in the United States as one of their instruments for return migration to Mexico.

4.1 U.S. immigration enforcement as an instrument for return migration

The sudden increase in enforcement from 2005 to remove unauthorized immigrants created a hostile environment for all migrants, irrespective of their legal status. This led to shortened migration trips and a greater number of decisions to return. I use immigration enforcement as a shock that made migrants' decisions to stay uncertain and increased return to Mexico. I use the shift-share instrument variable (SSIV) approach for my identifying variation.

I use four shock measures from the U.S. enforcement policy data, which comes from the Urban Institute's State Immigration Policy Resource. The policy shocks are distributed across 50 states and the District of Columbia, implemented at different times over five years (2005–2010), as shown in Figure A.1 (Appendix). The four policies used are a) 287(g) agreement,[14] b) 287(g) jail agreement,[14] c) Secure Communities program,[15] and d) E-Verify mandate.[16]

To create the instrument, first, I capture the policy score PS_k^s under each policy p for a U.S. state s:

$$PS_p^s = \frac{\sum_{y=0}^{N} P_{py}^s}{N} \tag{1}$$

$P_{py}^s \in (0, 1)$ is a score[17] given for each policy p at year y in U.S. state s. N is the maximum number of years each policy p was active in the United States during

[14]Either a state agency or some or all of the counties in the state with the highest immigrant population have a 287(g) task force agreement and jail agreement to access federal immigration databases and arrest and detain individuals for suspected immigration violations.

[15]Through Secure Communities, the FBI shares the fingerprints it receives from local law enforcement agencies with immigration enforcement agencies for checks against immigration databases. The immigration officials then decide on an enforcement action, such as issuing a request for detaining.

[16]An electronic verification system that confirms the employment eligibility of workers.

[17]Score may be 0.5 for states where the policy was implemented to selected counties with high immigration.

2005–2010. Second, I combined the policies to create a synthesized score for each state:

$$SPS^s = \frac{\sum_{p=0}^{4} PS_p^s}{4} \tag{2}$$

SPS^s is the synthesized policy score for 4 policies for each state s in the United States.

In the final step to link the Mexican municipalities' exposure to these policies, I multiply the share of migrants from each municipality m to U.S. state s. Census data lack information regarding the exact location in which the return migrants lived during their stay in the United States. Therefore, to get information on the share of migrants from Mexican municipalities to the U.S. destination states (Figure 3), I use the Mexican consular identification cards[18] issued to Mexican living in the United States. These cards, available from 2008–2010, are provided to Mexican nationals residing in the United States. They include information about the individual's municipality of birth in Mexico and state of residency in the United States.[19] With this information, I link U.S. immigration enforcement policies to Mexican municipalities and create the instrumental variable $\textit{Immigration Enforcement Exposure}_m$:

$$\textit{Immigration Enforcement Exposure}_m = \sum_{s=0}^{51} \lambda_m^s * SPS^s, \quad \sum_{s=0}^{51} \lambda_m^s = 1 \tag{3}$$

where, λ_m^s is the share of migrants from each municipality m in Mexico living across the 50 U.S. states and the District of Columbia. $\textit{Immigration Enforcement Exposure}_m \in (0, 1)$, 1 being high exposure of a Mexican municipality to U.S. immigration enforcement. The exposure of Mexican municipalities to U.S. immigration enforcement is shown in Figure 4.[20]

One caveat in using consular cards to calculate the share of migrants from Mexican municipalities to U.S. states is that every migrant may not have the card. Approximately

[18]For a more comprehensive explanation of the consular identification cards, see Massey, Rugh, and Pren (2010).

[19]For municipalities where the number of consular cards were less than 100, I impute the weights using the state's average weight where the municipality is located.

[20]If from Oaxaca out of the total migrants, one-third move to Texas, and two-thirds move to California. The *Immigration Enforcement Exposure* score for Oaxaca will be $\frac{1}{3} * 0.70 + \frac{2}{3} * 0.90 = 0.83$. 0.70 and 0.90 being the SPS^{Texas} and $SPS^{California}$, respectively.

2.3 million consular identification cards out of approximately 12 million Mexican-born immigrants are available in 2010 (Figure 1). Therefore, the share of migrants from each Mexican municipality in the U.S. state may under-represent the actual migration flows. However, Caballero, Cadena, and Kovak (2018) and Bucheli and Fontenla (2019) find a high correlation between each U.S. state's share of consular cards and its share of the non-U.S. citizen Mexican population in the 2000 and 2010 censuses and conclude that the share provided by the Mexican identification consular card data are not biased.

I obtain exogenous variation in return migration in households by employing instruments that capture the exposure of Mexican municipalities to U.S. state immigration enforcement in 2005–2010 when the migrants returned. This means that we identify those households where the probability of return migration is influenced by the U.S. immigration enforcement, thus estimating a local average treatment effect (LATE) (Imbens, Angrist, et al., 1994). The instrumental variable is uninformative of migrants who will never return (never takers) and who will always return (always takers), irrespective of immigration enforcement.

4.2 First Stage

In the first stage, I model the probability of a household having a return migrant using municipality-level variation in the exposure to U.S. immigration enforcement as the exogenous shock. As noted in the previous section, a more stringent enforcement policy creates a hostile environment for the immigrant population. We can observe that more migrants are returning during 2005–2010, particularly after 2007 (Figure 1). Greater enforcement may increase return migration from the United States; however, enforcement could also decrease migration and, therefore, decrease remittances. This is one of the reasons why I compare households with only return migrants to non-migrant households. I also recognize that stricter enforcement in the United States discouraged individuals from migrating, thereby increasing the number of non-migrating households. However, relative to the non-migrant households, return migrant households are higher in municipalities with higher exposure to immigration enforcement.

The rates of return migrants in the households seem randomly distributed. This is demonstrated in Figure 5, which shows no clear pattern in the sample's share of households with return migrants. I further address the potential endogeneity of return migration by controlling for an extensive set of household- and municipality-level characteristics.

The main variable of interest is a dichotomous variable $RetMig$, for which there is an underlying latent variable $RetMig^*_{ihmr}$. In practice, $RetMig^*_{ihmr}$ is unobservable. I only observe the dichotomous variable $RetMig$, as defined by:

$$RetMig = \begin{cases} 1 & if \quad RetMig^*_{ihmr} > 0 \\ 0 & otherwise \end{cases} \tag{4}$$

Therefore, I estimate the first stage by predicting return migration in a household using a logistic function in which the probability that there is a return migrant in household h, of child i, in municipality m, in region r is

$$P(RetMig_{ihmr} = 1) = \frac{e^{W\tau}}{(1 + e^{W\tau})} \tag{5}$$

where,

$$W\tau = \tau_0 + \tau_1 ImmEnf_{mr} + \tau_2 X_{ihmr} + \tau_3 H_{hmr} + \tau_4 M_{mr} + \omega_r + \mu_{ihmr} \tag{6}$$

$ImmEnf_{mr}$ is the instrumental variable defined as the exposure of Mexican municipalities to immigration enforcement in the United States. X_{ihmr}, H_{hmr}, and M_{mr} are vectors of individual, household, and municipality-level controls, respectively. ω_r is a vector of the regional dummy variable.[21]

4.2.1 Validity of the instruments

A valid instrument must fulfil two conditions: the relevance condition (i.e., the instrument has a high predictive power for the endogenous variable of interest) and the exclusion re-

[21]The regions are North, Central, West, East, South

striction (i.e., the instrument is uncorrelated with unobservables affecting the *school–work tradeoff* and *selection into employment types*). Table 2 reports the first stage of the two dependent variables. I divide the results into three columns: full sample, female sample, and male sample. I also divide the table into two panels, as the number of observations for the two dependent variables is different. Panel A shows the results for the dependent variable *school–work tradeoff*, and Panel B consists of results from dependent variable *selection into employment types*. For both the first stages, we observe a high χ^2. Specifically, χ^2=25.61 and χ^2=24.53 for our full sample models, which is statistically significant at the 1% level of significance. This suggests that our instrument satisfies the relevance condition and is unlikely to be a weak instrument.

I proceed to discuss some potential threats to the validity of the instrument. The possible sources of endogeneity, in this case, are reverse causality and unobserved heterogeneity. Reverse causality may bias the estimates if the return migration decisions in the households in the sample are determined to some degree by the school–work tradeoff or type of work decision of the child in the household. This can happen, for example, if the migrant returns because their child has terminated schooling or dropped out of school and entered the labor market. As the identification strategy relies on municipality-level variation in exposure to US interior enforcement, the instrument is unlikely to be correlated with individual-level heterogeneity. However, households may sort into municipalities with favorable labor market conditions and social infrastructure. This, however, is unlikely to substantially affect the estimates as only 4.39% of the children in the sample lived in a different municipality five years ago.

Unobserved heterogeneity is likely to bias the results if omitted variables such as household's unobserved preferences toward children's school–work decisions and occurrence of return migration simultaneously affect the outcomes of interest. One of the concerns is that the probability of return migration in households is non-random and may be correlated with local child labor conditions. To address this, I include a set of municipality-level controls in both the first- and second-stage equations, which include the municipalities' crime, income, and physical infrastructure for 2010. Another threat to the validity of the instrument arises if there is a pattern in the municipality-level exposure to U.S. immigration enforcement. For instance, Figure 4 displays a higher intensity of exposure to immigration enforcement in the northwest region of Mexico. This is likely because the share of migrants from municipalities close to the border is higher in U.S. states with more stringent enforcement policies. I conduct two checks to address this issue. First, I estimate the models by excluding municipalities in states that share a border with the United States. Second, I exclude the municipalities in the northwest region of Mexico. The results are shown in Table 7, where we observe that the estimates are not substantially affected by these exclusions. Therefore, it is unlikely that the geographic patterns in the instrument bias the estimates.

The evidence so far suggests that non-random exposure to immigration enforcement for the municipalities is unlikely to drive the results, but I recognize that I cannot completely rule out this possibility. Therefore, I perform another check to strengthen the identification strategy. My instrument, immigration enforcement exposure, is a shift-share instrument[22] which relies on exogenous shocks. Borusyak, Hull, and Jaravel (2018) demonstrate that a shift-share instrument is valid if, conditional on the shares, the set of shocks is as good as randomly assigned. Therefore, the instrument will satisfy the exclusion restriction under the assumption of randomness of the shock (enforcement policy, in my case) assignment. The randomness assumption could fail if the enforcement intensity across U.S. states is correlated with municipality characteristics. The cross-sectional variation in enforcement policies between states may be caused due to variation in the share of migrants. For instance, states that attract migrants from particular municipalities adopt stricter enforcement. To test this assumption, I run regressions at the municipality level for each of the municipality characteristics from Equation 6 on U.S. immigration enforcement (Table A.4). We can observe that, except for the percentage of households receiving remittances, all municipality-level characteristics are balanced across the immigration enforcement. The negative coefficient on the percentage of households receiving remittances indicates that municipalities exposed to higher levels of enforcement have

[22]An instrumental variable created with a set of shocks ("shifters") weighted by sector "shares".

fewer households receiving remittances. Therefore, I control for the municipality-level percentage of households receiving remittances in the regressions.

4.3 Second Stage

A child in a household can only be at school, only at work, doing both, or neither at school nor work. The decision to send a child to school or to work is not independent of each other. Therefore, to make the relationship between the decisions explicit and allow for the interdependence of the alternatives, I create a variable *school–work tradeoff* with four categories as mentioned above. Employment outcomes are also divided into four broad categories in the census: non-participants,[23] self-employed, wage-salaried, and unpaid workers. Therefore, I estimate the outcome equation predicting the *school–work tradeoff* and *selection into employment types* by employing a multinomial logistic (MNL) model,[24] in which the probability of a child i in household h, municipality m, and region r being in dependent variable status d, is

$$P^d_{ihmr} = \frac{e^{V^d_{ihmr}}}{\sum_{n=1}^{4} e^{V^n_{ihmr}}}, \text{where} \quad d \quad \in \quad \{1,2,3,4\} \quad \text{and} \tag{7}$$

where the indirect utility of adolescent child i residing in household h, in municipality m, in region r, and selecting school–work choice d, V^d_{ihmr}, is given by,

$$V^d_{ihmr} = \beta^d_0 + \beta^d_1 RetMig_{ihmr} + \beta^d_2 X_{ihmr} + \beta^d_3 H_{hmr} + \beta^d_4 M_{mr} + \beta^d_5 \hat{\mu}_{ihmr} + \omega_r + \upsilon_{ihmr} \tag{8}$$

Under the Random Utility Model (RUM) framework, an adolescent child is assumed to select into school–work choice or employment types d for which they receive the highest

[23]Independent of going to school or not.

[24]As a robustness check, I also use a bi-probit model described in Appendix Section 12.2. The results are reported in Table A.7.

utility. Thus, the probability that an adolescent i will select into type d is:

$$P^{d}_{ihmr} = Pr(V^{d}_{ihmr} > V^{e}_{ihmr}) for\ all\ e \neq d \tag{9}$$

The choice between school and work, and selection into employment types are fundamentally different states representing different behaviors and decisions. We, therefore, employ Equation 8 and 9 to estimate two models, one to specify their choice between school and work, and the other to look into what type of work adolescents select.

The individual- and household-level controls are age, sex, mother's hours of work, mother's education, household wealth index, and the number of family members. The municipality-level controls are the 2010 percentage of households receiving remittances, income per capita, number of homicides, schools per 1,000 population in the municipality, and log of expenditure. I also control for region fixed effect, with binary indicators for five categories: North, Central, West, East, and South.

5 Results

I begin by presenting the four-state model of school, work, neither, and both, in Panel A of Table 3, which reports the estimated average marginal effects of having a return migrant in the household on the school–work choice of the adolescent. These marginal effects represent the likelihood that a child in a return migrant household is in each of the four categories relative to a child in a non-migrant household. Column (1) shows the results for the full sample, and columns (2) and (3) show results for the male and female child samples, respectively. In all three samples, children in return migrant households are significantly more likely to go to school than their non-migrant household counterparts. The male population point estimate (Column 3) for school, which is much larger than the female population results (Column 2), indicates that the effect of having a return migrant in the household is greater for an adolescent male. The difference between the likelihood of children in non-migrant and return migrant households neither attending school nor working is insignificant for all samples. However, overall, I see a shift in the distribution from working, being idle, or doing both, toward solely attending school.

While return migrants appear to decrease their labor market participation, the type of occupation in which they are employed also provides interesting insights. Panel B of Table 3 reports the average marginal effects of having a return migrant in the household on the likelihood of belonging to each of the four states of employment. These results, once again, reflect the probability that children in return migrant households are in each of the four job categories compared to children in non-migrant households. Focusing on the entire sample (column 1), we can observe that children in return migrant households are 26 percentage points more likely to be in the non-participation state than non-migrant households. The effect is significant at the one percent level. While Panel A of Table 3 indicates that children in return migrant households are less likely to work than their non-migrant household counterparts, Panel B shows that adolescents in return migrant households are more likely to be self-employed. The decrease in the probability of working from Panel A is mainly accounted for by a 25.3 percentage point decrease in wage or salaried work and a 6.61 percentage point decrease in unpaid work for the full sample. One interesting result to focus on is that self-employment in return migrant households for children is 5.2 percentage points greater than non-migrant households. The plausible explanation would be that all the capital and savings accumulated during the migrants' stay in the United States are invested when the migrants return to their households' business (Batista et al., 2017; Dustmann & Kirchkamp, 2002; Marchetta, 2012; Wahba & Zenou, 2012).

Although from column 2 we do not find any significant differences between female adolescents in return migrant and non-migrant households in terms of the likelihood of being self-employed or working at an unpaid job, I find a 19.6 percentage points decrease in wage work for female adolescents in a return migrant household. Comparing the female sample to the male sample (Columns 2 to 3) from Panel B of Table 3, I find the effect of being a self-employed adolescent child in a return migrant household is higher by approximately 6 percentage points. This is consistent with the fact that in developing countries a female child is more likely to work as an unpaid worker in the household, and the household is less likely to invest in the female child as a self-employed person than a male child. Thus, as with the probability of participation in the labor market, the decrease in adolescents working in wage/salaried jobs or unpaid work is partially mediated by the positive effect of return migration in the household on human capital accumulation through schooling. This indicates that having a return migrant in the household directly pulls adolescents from work (possibly due to savings accumulated from the return migrant) as well as indirectly due to the positive effect of school attainment. Overall, we observe that the effects of being in a return migrant household are lower in magnitude for girls relative to boys. While I can only observe these children from age 12 in their working life, these indirect effects may represent a longer-term improvement in the quality of employment outcomes in return migrant households.

Thus, while having a return migrant in the household decreases the probability of working for both boys and girls, the selection into employment types matters in explaining the quality of their jobs. Having a return migrant in the household significantly raises the likelihood that a child will be self-employed and decreases the likelihood of being a wage/salaried worker or working at an unpaid job. However, for a female adolescent, having a return migrant in the household seems to have no statistically significant impact on whether she selects into self-employment or unpaid work, even if it does increase the probability that she is not working. The observed differences between males and females adolescents reflect gender differentials in the effect of a return migrant in the household based on traditional, gender-based occupational segregation.

To observe the heterogeneity of the results by age, I interact the age of the child with the independent variable, return migration in the household. Figures 6 - 9 show[25] the average marginal effects of having a return migrant in the household on the school–work decisions and selection into employment types of the child by age. We can observe that the differential effect of having a return migrant in the household compared to non-migrant households increases sharply for only attending school and decreases for only working. The size of the effect seems to increase with age for each of the outcome categories,

[25]Table A.5 and Table A.6 in the appendix present the coefficients.

although more sharply for school only and work only. We can also observe that for children in return migrant households, the probability of performing both activities decreases at an increasing rate with age for an adolescent relative to non-migrant households, although the effects are only significant for males Figure 7. The marginal effects on the probability of only attending school and only participating in the labor market are larger in magnitude for male than for female adolescents of all ages. For the employment outcomes, I see a distinct increase in the negative effect on the probability of wage/salaried work and unpaid work with age. However, disaggregating the effects by age does not yield significant marginal effects on the probability of non-participation and self-employment. Similar to the school–work tradeoffs, we see that the marginal effects are larger in magnitude for males of all ages.

6 Robustness

In this subsection, I carry out several robustness checks. First, I re-define unpaid family work as non-participation in the labor force. Census data consider the children engaged in unpaid family work as participating in the labor market. As per the general convention, unpaid workers performing domestic duties in their households are considered non-participants. Unfortunately, I cannot verify whether the unpaid work is in their household or outside the homes. Nevertheless, I perform a robustness check by including the unpaid family workers as non-participants. The estimates are shown in Table 4. These results are nearly identical to the main results in Panel A of Table 3.

Second, I break down employment into a total of six categories. Wage/Salaried work is further broken down into two categories: White- or blue-collar and day laborer. Also, self-employment is subcategorized into employer and working on own account. The estimates are shown in Table 5. The increase in self-employment from Panel B of Table 3 is driven more by working on own account than by being an employer. Moreover, the decrease in wage/salaried work is influenced equally by a decrease in the two subcategories. Having a return migrant in the household decreases the probability of being a day laborer for the male sample by 20 percentage points. However, the decrease in white- or blue-collar jobs is insignificant for the male sample. The differences in the magnitudes of the marginal effects on the probability of being a day laborer across gender may be attributed to the fact that the most hazardous jobs are performed by day laborers, of which men are a higher proportion. Therefore, a return migrant in the household induces a decrease in wage/salaried jobs by decreasing the probability of working as day laborers among male adolescents and reducing the probability of white or blue-collar jobs among female adolescents.

Third, for the variable *selection into employment types*, census data identifies children as *not in the universe* if they are not in the labor force or they are in the labor force but unemployed. I consider them as non-participants as they are not working. Therefore, to disentangle the effect of children unemployed and not in the labor force, I check the results by dividing the non-participant group into those not in the labor force and those unemployed. The overall results remain the same, as reported in Table A.3

I also conduct several other robustness checks using alternative sample selection criteria. The results are robust to excluding urban areas, states with high migration, states with high return migration, and excluding households with domestic return migrants, as shown in Table 6. There is evidence for why researchers should consider treating urban and rural child labor differently in the literature. Children work more in rural than in urban areas.[26] Domestic work, a family business, or in my case, unpaid work, is highly prevalent in rural areas (Edmonds, 2007). Moreover, urban areas show the highest levels of development and may also have characteristics that pull return migrants back. Therefore, I omit urban areas from the sample and find from Table 6 columns (1)-(3) that the estimated impact is still significant in rural areas and greater in magnitude. The only discernible difference is the significant marginal effect on unpaid work for the female sample. However, these estimates must be interpreted with caution, considering the low instrument relevance in the first stage.

One caveat in the analysis is that I am unable to account for migratory networks,

[26]Edmonds and Pavcnik (2005) find that of children between the age of 5–14 engaged in market work, 31 percent are from rural areas compared to 19 percent from urban areas.

which seem to be significant in Mexico (Munshi, 2003a; Woodruff & Zenteno, 2001). With the completion of the western section of the transcontinental railroad in 1885, migration from southern Mexico to the United States became simpler. Since then, Mexican workers were extensively recruited, particularly in mining and agriculture in the United States, as labor migration from China and Japan ceased (Office, 2021). This pattern continued during the first half of the twentieth century, particularly during the 1942–1964 Bracero Accord (temporary labor arrangement) (Cardoso, 1980). Between 1951 and 1962, four southwestern Mexican states–Jalisco, Michoacan, Guanajuato, and Zacatecas–accounted for almost half of all migration (Craig, 2014). Eight states –Aguascalientes, Jalisco, Guanajuato, San Luis Potosi, Michoacan, Zacatecas, Nayarit, and Colima–continue to provide the majority of Mexican migrants to the United States (Durand, Massey, & Charvet, 2000; Munshi, 2003a). These states are characterized by agriculture and manual labor as the dominant occupations, accompanied by low education levels. More extensive networks from these states are linked with reduced migration costs and should result in an increase in future migrants (Carrington, Detragiache, & Vishwanath, 1996; Kanbur & Rapoport, 2005; Munshi, 2003b). The return migration will also be high in those regions (Waddell & Fontenla, 2015), as return migration costs will be low, benefiting lower-income individuals disproportionately (McKenzie & Rapoport, 2007; Orrenius & Zavodny, 2005). To account for the potential bias resulting from the location choice of low-skilled return migrants, who may have lower savings and a higher probability of sending children to the United States for work, I omit states with high migration rates, as shown in Munshi (2003a). Table 6 (columns 4-6) shows that the estimates are consistent with the main results. The non-sensitivity of the results to excluding states with high rates of migrants also strengthens the argument for the satisfaction of exclusion restriction. The dominant destinations for migrants from these eight Mexican states are California and Texas (Figure 3). Additionally, these states had high enforcement policies in effect (Figure A.1). Since the instrument, U.S. immigration enforcement, is likely to be higher in these states, I posit that any potential correlation between the instrument and unobservables affecting local labor market conditions is unlikely to drive the results.

Domestic return migration is highly prevalent in Mexico, as is domestic migration (Nobles, 2006). The working sample contains households with individuals residing in other states five years before the sample period. Since domestic migrants could also accumulate savings and human capital during their stay in other states, domestic migration experiences may drive some of the observed effects. I explore whether the effect of domestic return migration confounds the effects of international return migration by omitting the households with domestic return migrants. The results from Table 6 (Columns 13–15) show that omitting households with domestic return migrants does not substantially change the main results. This rules out the possibility that domestic return migrants might drive the results since I only focus on U.S. return migrants. Moreover, Antman (2012) recognizes the causal effects of domestic and international migration on schooling and finds no major influence of domestic migration. This may be because domestic migrants' income, accumulated savings, or developed social norms are different from international migrants, and they are not as completely isolated from their homes as are foreign migrants.

As seen from Figure 4 the exposure to U.S. interior enforcement is high in the northwestern region. Additionally, proximity to the U.S.–Mexico border affects the cost of return migration. Therefore, to check the sensitivity of the estimates, I exclude the northwestern states and states that share a border with the United States. Table 7 demonstrates that this exclusion criterion does not change the estimates. This provides us sufficient evidence that closeness to the border is unlikely to confound my results. This also supports the argument that the instrument, U.S. immigration enforcement, is not likely to affect adolescent school–work choices through correlation with border proximity or geographic patterns.

Table 8 investigates whether the results are sensitive to different age ranges in the sample. Since migration among adolescents and young adults takes place by the age of 16 years (Hanson & McIntosh, 2009), the decrease in labor market participation may be driven by younger cohorts (age <16). Also, Mexico's Federal Labor Law prohibits children under the age of 16 from participating in what they call "unhealthy or hazardous work."[27] To get a clear idea, I segregate the data as shown in Table 8 into age 12–15 (columns 4–6) and age 16–19 (columns 7–9). Due to the age of 16 being a crucial cutoff, I expect two things. First, as wage/salaried work falls under "unhealthy or hazardous work," the difference of an adolescent in a return migrant household to that of an adolescent in a non-migrant household will be less for age group 12–15 than for age group 16–19. We can verify the statement from Table 8, where we observe the coefficient for wage/salaried work is -0.149 for age group 12–15 and -0.402 for age group 16-19. Second, with more migration occurring from age 16, the difference in the coefficient for school should be greater for age group 16–19 compared to 12–15. The coefficient for school from Panel A, columns 4 and 7, verifies the pattern stated above. I also conduct other sensitivity tests for my arguable adolescent definition (age 12–19) by keeping adolescents aged 12–18 (columns 1-3). The coefficients remain consistent with the main results from Table 3.

7 Heterogeneity Analysis

The impact of a return migrant in the household may vary by household wealth since poorer households are more likely to be liquidity constrained and, therefore, children in poorer households are more likely to terminate schooling and enter the labor market. In the absence of complete information about household income, I use the wealth index as a proxy for the socio-economic status of the household. I investigate the heterogeneity across wealth status by interacting the household wealth index with the endogenous variable, return migrant in the household. Figures 10 –13 demonstrate the heterogeneous effect of having a return migrant in the household across the household wealth index. We can observe that the marginal effect of a return migrant is larger in magnitude for the poorer households for most of the outcome categories, except for the category *both* from *school–work tradeoff*, and non-participation and unpaid work from *occupational choices*, which remain flat across the wealth distribution. Specifically, the marginal effects are

[27] This work is described as something harmful to the child's health, including working with various chemicals and nightwork in the industrial sector.

attenuated for wealthier households.

Overall, we observe that the probabilities of attending school and working as well as the occupational choices are less affected by the presence of a return migrant in wealthier households. This finding corroborates my hypothesis that poorer households are financially constrained, with limited access to savings and credit, and are, therefore, more likely to reap the higher marginal returns.

8 Discussion

In this section, I discuss some possible explanations for the observed effects. The results indicate that with a return migrant in the household, there is a shift from labor market participation, neither school nor working, or both toward an increase in only school attendance. As I lack information on remittances or savings and the inability to quantify social norms accurately, I cannot formally test the underlying mechanisms.

I speculate that income increases resulting from wage increase (Campos-Vazquez & Lara, 2012; Lacuesta, 2010; Reinhold & Thom, 2013; Wahba, 2015; Wahba & Zenou, 2012), accumulated savings or financial capital (Ahlburg & Brown, 1998; McCormick & Wahba, 2001; Thomas, 2008), and occupational mobility (El-Mallakh & Wahba, 2021) relax credit constraints and, therefore, households tend to pull the working children out of the labor force and instead invest in their human capital accumulation. The observed effects seem to be consistent with a positive income effect, considering that schooling is a normal good. The fact that we observe larger effects at the lower ends of the wealth distribution indicates that the presence of a return migrant relaxes income constraints, which likely more than compensates for the drop in remittances arising due to the cessation of the migration experience.

Regarding occupational choices, I find a decrease in wage/salaried work and unpaid work and an increase in self-employment of adolescents. Empirical evidence indicates working overseas allows migrants to gain new skills and build human capital (Beine et al., 2011, 2008); therefore, they are more likely to participate in entrepreneurial activities and climb up the occupational ladder when they return. Specifically, El-Mallakh and Wahba (2021) find that return migration increases the likelihood of upward occupational mobility, for example, from initial low-skilled blue-collar jobs to high-skilled blue-collar jobs or from high-skilled blue-collar jobs to low-skilled white-collar jobs. Such occupational mobility of the return migrants (mostly household heads or fathers) may induce adolescents to be self-employed rather than working in wage/salaried jobs, with larger decreases in the probability of working as day laborers among boys and in the probability of white- or blue-collar jobs among female adolescents.

Additionally, social norms gathered during their stay abroad may also be a possible explanation for the positive effects, although I cannot explicitly test this channel. Previous studies that demonstrate the transfer of migration experience-induced social norms lend support to my assumption. For instance, Bertoli and Marchetta (2015) find that Egyptian returnees have a higher number of children relative to the non-migrants, closer to the fertility level of the destination Arab countries. Other types of norms include traditional gender norms influencing female empowerment (Tuccio & Wahba, 2018) and pro-social conduct and community involvement (Nikolova, Roman, & Zimmermann, 2017). On the whole, available evidence suggests that return migration is a channel of tranmission of social norms.

9 Conclusion

The vast literature on the effects of migration from a developing to a developed country indicates brain drain, which has been a cause of concern among policymakers. In this context, the return of migrants from a developed country like the United States to an origin country such as Mexico is an important case to explore, considering the increasing rate of return migration from the United States to Mexico since 2007. This study is the first to explore the causal relationship between return migration and children's school–work and occupational choices in the household. I use U.S. immigration enforcement as an exogenous variation to address the endogeneity of return migration in households. Using a control function approach, my results provide evidence of an increase in schooling and a decrease in work for children aged 12–19 in households with return migrants relative to non-migrant households. Concerning occupational status, I find an increase in non-participation and self-employment and a decrease in wage/salaried work and unpaid work for children in return migrant households. However, the magnitude of the effects differs across gender, with larger positive effects among male children than among female children. Moreover, the marginal effects of a return migrant in the household are attenuated among wealthier households. Since poorer households are liquidity constrained, lack access to credit, and have lower preferences for their children's human capital accumulation, I hypothesize that the estimates from the main model (Table 3) are influenced by the transfer of accumulated savings and human capital from abroad, the improved labor market opportunities for return migrants in Mexico, and social norms. One of the limitations of this study is that, in the absence of information on remittances, I am unable to disentangle the effects of decreased remittances and the effects of increased savings. I do not, however, claim that these are the only mechanisms underlying the observed effects.

The findings contribute to the scarce literature on the effects of return migration on the human capital and labor outcomes of children in the household. Although I cannot explicitly characterize occupations as formal or informal, my results imply a lower likelihood of working in poor-quality, low-skilled jobs. The Federal Labor Act in Mexico bans working for children under 14 years of age. In addition, children under the age of 16 are not eligible to engage in so-called "unhealthy or dangerous jobs." Banning child labor has not worked fully in Mexico, as children in their adolescence engage in income-generating activities due to the need to survive. Banning child labor in manufacturing sectors would probably send children back to agricultural work (Basu, 1999), which is likely to decrease schooling. Therefore, highlighting the positive role of return migrants in the labor market outcomes of adolescents is of policy relevance in the context of Mexico.

Although my estimates pertain to the short-term effects of return migration, they have the potential to inform policymakers on the possible negation of brain drain. The paper suggests return migration from a developed to a developing country as a mechanism through which migrant flows may benefit origin developing countries worldwide. Policies aimed at assisting the reintegration of return migrants in local markets and employing the human, physical, and social capital accumulated from abroad may substantially improve the quality of education and can act as a tool to reduce child labor.

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10 Tables

Table 1: Means by type of Household

	Full Sample	Non-migrant HH	Return-migrant HH	Difference
	(1)	(2)	(3)	(4)=(3)-(2)
	Panel A: Dependent Variable			
School Work Status				
School	0.712	0.713	0.633	-0.079***
Work	0.123	0.122	0.161	0.039***
Neither	0.126	0.126	0.155	0.029***
Both	0.040	0.040	0.051	0.011***
Occupational Choice				
Non-Participation	0.838	0.839	0.788	-0.050***
Self-Employed	0.019	0.019	0.022	0.003
Wage Salaried	0.125	0.124	0.162	0.037***
Unpaid Work	0.018	0.018	0.028	0.010***
	Panel B: Independent Variable			
Age	15.306	15.306	15.295	-0.011
Female	0.483	0.482	0.490	0.007
Mother's Hrs work/week	15.882	15.904	14.256	-1.648***
Number of own family members	5.523	5.511	6.365	0.854***
HH wealth index	1.013	1.012	1.087	0.074***
Mother's Education				
< Primary	0.256	0.255	0.293	0.038***
P completed	0.540	0.539	0.604	0.065***
S completed	0.146	0.147	0.083	-0.064***
U completed	0.058	0.059	0.020	-0.038***
Urban	0.739	0.741	0.579	-0.163***
% of HH Remittances (2010)	3.815	3.765	7.487	3.722***
Ln(Income per capita) (2010)	9.545	9.547	9.383	-0.164***
Number Homicide (2010)	133.862	134.270	103.910	-30.360***
Schools per 1000 people	2.279	2.270	2.934	0.663***
Ln(Municip Expend) (2010)	19.871	19.880	19.201	-0.679***
Region				
North	0.235	0.235	0.173	-0.062***
Central	0.305	0.305	0.318	0.013**
West	0.136	0.136	0.195	0.060***
East	0.151	0.151	0.173	0.022***
South	0.173	0.173	0.140	-0.033***
Observations	1,292,375	1,269,469	22,906	

Note: The table reports means for full sample, and by type of household. Panel A shows the means for the dependent variables *Selection into Employment Types* and *school–work status*. Each dependent variable consist of four categories. Panel B shows the means for independent variables. Column (1) reports the means for the full sample. Columns (2) reports means for household with non-migrants. Columns (3) reports means for household with return migrants. Columns (4) report the difference of means between return migrant household and non-migrant household and its statistical significance by performing a t-test with sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

10.1 First Stage

Table 2: First-Stage Estimated Marginal Effects of Exposure to U.S. immigration enforcement on Return Migration in Households

	Full Sample	Female	Male
	(1)	(2)	(3)
PANEL A: School Work status			
U.S. Immigration Enforcement (05-10)	0.0111***	0.0114***	0.0108***
	(0.00220)	(0.00314)	(0.00307)
Instrument Relevance			
χ^2	25.61	13.10	12.52
p-value	0.000	0.000	0.000
Observations	1291474	617458	674016
PANEL B: Selection into Employment Types			
U.S. Immigration Enforcement (05-10)	0.0109***	0.0114***	0.0104***
	(0.00220)	(0.00314)	(0.00308)
Instrument Relevance			
χ^2	24.53	13.10	11.52
p-value	0.000	0.000	0.001
Observations	1292375	618871	673504
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Panel A shows the results for outcome variable school–work status. Panel B shows the results for selection into employment types. Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

10.2 Second Stage

Table 3: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff and labor outcomes of children

	Full Sample	Female	Male
	(1)	(2)	(3)
PANEL A: School-Work Tradeoff			
School	0.254***	0.157**	0.344***
	(0.0520)	(0.0613)	(0.0836)
Work	-0.0986***	-0.0797*	-0.105*
	(0.0367)	(0.0414)	(0.0609)
Neither	-0.0402	-0.0540	-0.0426
	(0.0348)	(0.0503)	(0.0488)
Both	-0.115***	-0.0230	-0.196***
	(0.0302)	(0.0312)	(0.0530)
Observations	1291474	617458	674016
PANEL B: Labor Outcomes			
Non-Participation	0.267***	0.162***	0.350***
	(0.0450)	(0.0514)	(0.0746)
Self-Employed	0.0520***	0.0197	0.0800***
	(0.0152)	(0.0181)	(0.0264)
Wage/Salaried Worker	-0.253***	-0.196***	-0.299***
	(0.0425)	(0.0491)	(0.0694)
Unpaid Worker	-0.0661***	0.0145	-0.132***
	(0.0129)	(0.0124)	(0.0222)
Observations	1292375	618871	673504
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Panel A shows the results for outcome variable school–work status. Panel B shows the results for selection into employment types. Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

10.3 Unpaid Family Work in Non-Participation

Table 4: Average Marginal Effects of a Return Migrant in the Household on Selection into Employment Types

	Full Sample	Female	Male
	(1)	(2)	(3)
	Labor Outcomes		
Non-Participation	0.211***	0.183***	0.227***
	(0.0443)	(0.0507)	(0.0733)
Self-Employed	0.0511***	0.0189	0.0800***
	(0.0152)	(0.0182)	(0.0265)
Wage/Salaried Worker	-0.262***	-0.202***	-0.307***
	(0.0427)	(0.0492)	(0.0697)
Observations	1292375	618871	673504
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

10.4 Selection into employment type: Detailed

Table 5: Average Marginal Effects of a Return Migrant in the Household on Selection into Employment Types

	Full Sample	Female	Male
	(1)	(2)	(3)
Labor Outcomes			
Non-Participation	0.241***	0.147***	0.319***
	(0.0456)	(0.0514)	(0.0759)
Employer	-0.000285	0.00222+	-0.00391
	(0.00274)	(0.00145)	(0.00541)
Working on own account	0.0500***	0.0161	0.0794***
	(0.0149)	(0.0181)	(0.0259)
White or blue collar	-0.104**	-0.151***	-0.0570
	(0.0421)	(0.0486)	(0.0685)
Day laborer	-0.120***	-0.0295***	-0.204***
	(0.0124)	(0.00756)	(0.0235)
Unpaid family worker	-0.0671***	0.0144	-0.133***
	(0.0129)	(0.0124)	(0.0222)
Observations	1292375	618871	673504
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Robustness checks

	Rural			W/O High Migration States			W/O High RM States 90P			W/O High RM State 75P			W/O Domestic RM HH		
	(1) Full Sample	(2) Female	(3) Male	(4) Full Sample	(5) Female	(6) Male	(7) Full Sample	(8) Female	(9) Male	(10) Full Sample	(11) Female	(12) Male	(13) Full Sample	(14) Female	(15) Male
PANEL A: School Work tradeoff															
School	0.641***	0.495***	0.770***	0.185***	0.0792	0.277***	0.104*	-0.0320	0.227***	0.0625	-0.0205	0.142*	0.248***	0.176***	0.304***
	(0.0631)	(0.0885)	(0.0889)	(0.0479)	(0.0594)	(0.0741)	(0.0546)	(0.0697)	(0.0791)	(0.0650)	(0.0905)	(0.0862)	(0.0553)	(0.0646)	(0.0892)
Work	-0.233***	-0.152**	-0.368***	-0.0730**	0.0165	-0.150***	-0.0399	0.0500	-0.125**	-0.0327	0.0369	-0.110*	-0.0945**	-0.0932**	-0.0768
	(0.0550)	(0.0675)	(0.0867)	(0.0334)	(0.0361)	(0.0555)	(0.0403)	(0.0488)	(0.0581)	(0.0500)	(0.0680)	(0.0648)	(0.0391)	(0.0435)	(0.0648)
Neither	-0.356***	-0.328***	-0.311***	0.0126	-0.0380	0.0592	0.0590*	0.0128	0.101**	0.0490	-0.00139	0.0959*	-0.0360	-0.0637	-0.0253
	(0.0528)	(0.0813)	(0.0677)	(0.0325)	(0.0488)	(0.0418)	(0.0340)	(0.0504)	(0.0448)	(0.0393)	(0.0588)	(0.0512)	(0.0366)	(0.0531)	(0.0513)
Both	-0.0522*	-0.0155	-0.0918*	-0.124***	-0.0577**	-0.185***	-0.123***	-0.0308	-0.203***	-0.0787***	-0.0149	-0.128**	-0.118***	-0.0191	-0.202***
	(0.0293)	(0.0240)	(0.0525)	(0.0267)	(0.0283)	(0.0454)	(0.0296)	(0.0313)	(0.0511)	(0.0305)	(0.0334)	(0.0519)	(0.0317)	(0.0313)	(0.0567)
Instrument Relevance															
First Stage χ^2	21.42	9.44	12.29	25.37	13.48	11.98	23.49	13.38	10.35	43.11	24.74	18.82	18.60	11.88	7.21
p-value	0.000	0.002	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.007
Observations	646201	306082	340119	1025993	490215	535778	1159081	553965	605116	970650	462729	507921	1201577	574062	627515
PANEL B: Selection into Employment types															
Non-Participation	0.284***	0.199***	0.379***	0.233***	0.0735+	0.374***	0.220***	0.0257	0.394***	0.169***	0.0176	0.316***	0.270***	0.174***	0.334***
	(0.0586)	(0.0724)	(0.0919)	(0.0418)	(0.0462)	(0.0688)	(0.0484)	(0.0570)	(0.0732)	(0.0586)	(0.0758)	(0.0814)	(0.0475)	(0.0528)	(0.0794)
Self-Employed	0.0910***	0.0274	0.157***	0.0335***	0.0256+	0.0372*	0.0392***	0.0299*	0.0460**	0.0516***	0.0253	0.0700***	0.0682***	0.0250	0.110***
	(0.0238)	(0.0191)	(0.0439)	(0.0128)	(0.0156)	(0.0212)	(0.0137)	(0.0171)	(0.0231)	(0.0144)	(0.0194)	(0.0242)	(0.0162)	(0.0189)	(0.0282)
Wage/Salaried Worker	-0.300***	-0.266***	-0.359***	-0.161***	-0.0893**	-0.219***	-0.164***	-0.0545	-0.262***	-0.141**	-0.0528	-0.227***	-0.261***	-0.207***	-0.300***
	(0.0552)	(0.0700)	(0.0863)	(0.0396)	(0.0442)	(0.0648)	(0.0463)	(0.0550)	(0.0693)	(0.0567)	(0.0741)	(0.0774)	(0.0447)	(0.0504)	(0.0733)
Unpaid Worker	-0.0752***	0.0398**	-0.177***	-0.105***	-0.00981	-0.192***	-0.0954***	-0.00109	-0.178***	-0.0797***	0.00993	-0.159***	-0.0773***	0.00839	-0.144***
	(0.0271)	(0.0163)	(0.0515)	(0.0126)	(0.0111)	(0.0218)	(0.0128)	(0.0121)	(0.0217)	(0.0136)	(0.0122)	(0.0235)	(0.0138)	(0.0128)	(0.0239)
Instrument Relevance															
First Stage χ^2	19.64	8.52	11.42	24.32	13.42	11.07	22.40	13.38	9.38	41.33	24.47	17.45	17.67	11.87	6.45
p-value	0.000	0.004	0.001	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.001	0.011
Observations	646281	306868	339413	1026571	491348	535223	1159814	555221	604593	971509	463938	507571	1202382	575370	627012
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Panel A shows the results for outcome variable school–work status. Panel B shows the results for selection into employment types. Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.Table report estimates for the rural sample (cols 1-3), excluding high migration states (cols 4-6), omitting high return migration states above 90th percentile (cols 7-9), omitting high return migration states above 75th percentile (cols 10-12), excluding households with domestic return migrants (cols 13-15).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Validity of Instrument

	W/O NorthWest			W/O Border State		
	(1) Full Sample	(2) Female	(3) Male	(4) Full Sample	(5) Female	(6) Male
	PANEL A: School Work tradeoff					
School	0.239***	0.118*	0.379***	0.343***	0.256***	0.440***
	(0.0534)	(0.0627)	(0.0892)	(0.0545)	(0.0641)	(0.0904)
Work	-0.0613+	-0.0687+	-0.0538	-0.131***	-0.141***	-0.131**
	(0.0378)	(0.0435)	(0.0646)	(0.0394)	(0.0479)	(0.0667)
Neither	-0.0678*	-0.0413	-0.122**	-0.107***	-0.102*	-0.125**
	(0.0364)	(0.0520)	(0.0521)	(0.0365)	(0.0522)	(0.0511)
Both	-0.110***	-0.00788	-0.204***	-0.104***	-0.0129	-0.183***
	(0.0313)	(0.0306)	(0.0581)	(0.0327)	(0.0321)	(0.0595)
Instrument Relevance						
First Stage χ^2	58.15	30.61	27.72	43.84	21.54	22.36
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1175733	562629	613104	1146321	548402	597919
	PANEL B: Selection into Employment types					
Non-Participation	0.214***	0.136***	0.282***	0.273***	0.216***	0.329***
	(0.0458)	(0.0529)	(0.0788)	(0.0476)	(0.0584)	(0.0812)
Self-Employed	0.0646***	0.0205	0.105***	0.0554***	0.0239	0.0831**
	(0.0171)	(0.0192)	(0.0313)	(0.0192)	(0.0208)	(0.0354)
Wage/Salaried Worker	-0.196***	-0.165***	-0.229***	-0.253***	-0.253***	-0.261***
	(0.0425)	(0.0502)	(0.0712)	(0.0440)	(0.0560)	(0.0728)
Unpaid Worker	-0.0825***	0.00832	-0.159***	-0.0757***	0.0137	-0.150***
	(0.0148)	(0.0142)	(0.0259)	(0.0152)	(0.0147)	(0.0266)
Instrument Relevance						
First Stage χ^2	55.55	31.12	24.75	42.17	21.77	20.56
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1176265	563813	612452	1146713	549527	597186
Controls	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓

Note: Panel A shows the results for outcome variable school–work status. Panel B shows the results for selection into employment types. Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

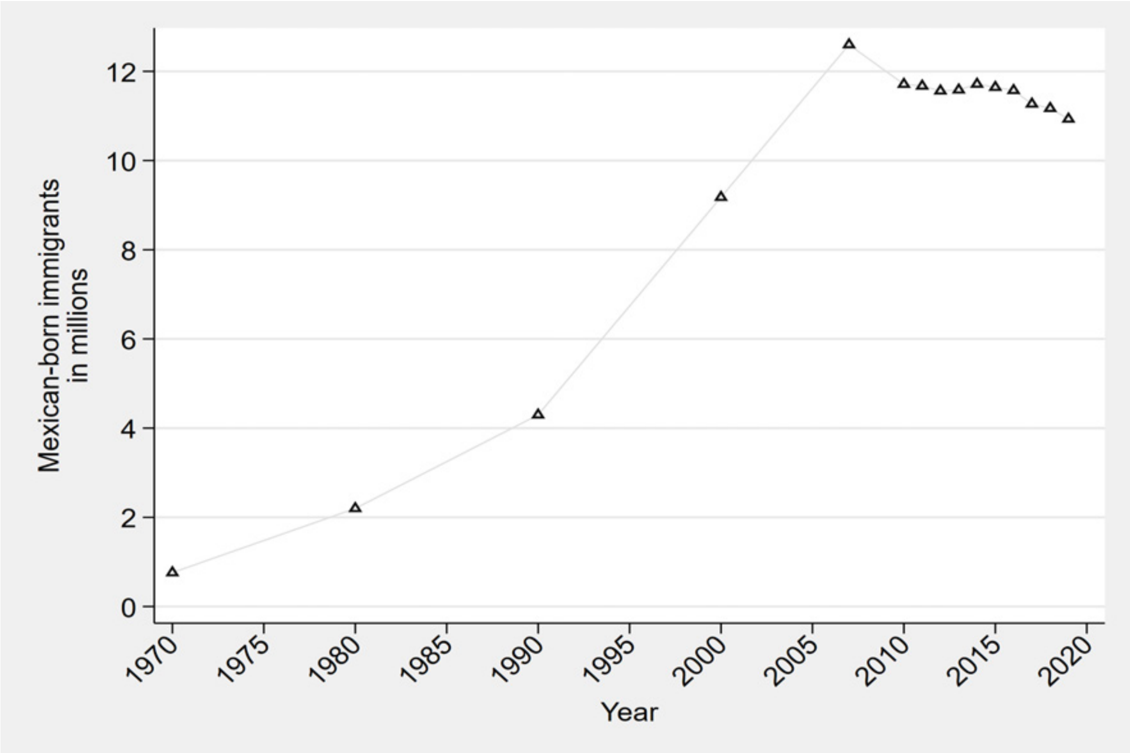
Table 8: Sensitivity test

	Age 12-18			Age 12-15			Age 16-19		
	(1) Full Sample	(2) Female	(3) Male	(4) Full Sample	(5) Female	(6) Male	(7) Full Sample	(8) Female	(9) Male
PANEL A: School Work tradeoff									
School	0.258***	0.145**	0.358***	0.217***	0.125*	0.309***	0.382***	0.267**	0.476***
	(0.0516)	(0.0633)	(0.0822)	(0.0560)	(0.0681)	(0.0932)	(0.0919)	(0.113)	(0.143)
Work	-0.0855**	-0.0742*	-0.0912+	-0.0326	-0.0472	-0.0378	-0.224***	-0.183**	-0.223*
	(0.0342)	(0.0391)	(0.0573)	(0.0261)	(0.0379)	(0.0441)	(0.0702)	(0.0814)	(0.115)
Neither	-0.0519	-0.0383	-0.0670	-0.0808**	-0.0302	-0.138**	-0.0393	-0.0835	0.00125
	(0.0362)	(0.0518)	(0.0512)	(0.0410)	(0.0542)	(0.0614)	(0.0593)	(0.0901)	(0.0784)
Both	-0.121***	-0.0329	-0.199***	-0.103***	-0.0478+	-0.134**	-0.119**	-0.000229	-0.255***
	(0.0308)	(0.0312)	(0.0550)	(0.0338)	(0.0309)	(0.0641)	(0.0509)	(0.0563)	(0.0863)
Instrument Relevance									
First Stage χ^2	20.26	10.30	9.99	12.99	4.37	8.80	13.03	9.87	3.91
p-value	0.000	0.001	0.002	0.000	0.037	0.003	0.000	0.002	0.048
Observations	1177844	566250	611594	708570	349324	359246	582904	268134	314770
PANEL B: Selection into Employment types									
Non-Participation	0.257***	0.157***	0.344***	0.161***	0.155**	0.192***	0.433***	0.271***	0.543***
	(0.0438)	(0.0503)	(0.0734)	(0.0410)	(0.0625)	(0.0690)	(0.0798)	(0.0953)	(0.129)
Self-Employed	0.0490***	0.0108	0.0798***	0.0279**	0.0217**	0.0438+	0.0651**	0.00277	0.113***
	(0.0148)	(0.0161)	(0.0270)	(0.0140)	(0.0109)	(0.0287)	(0.0264)	(0.0367)	(0.0405)
Wage/Salaried Worker	-0.233***	-0.165***	-0.294***	-0.149***	-0.184***	-0.156***	-0.402***	-0.294***	-0.472***
	(0.0411)	(0.0470)	(0.0679)	(0.0370)	(0.0613)	(0.0596)	(0.0768)	(0.0908)	(0.123)
Unpaid Worker	-0.0740***	-0.00204	-0.130***	-0.0399**	0.00749	-0.0800***	-0.0959***	0.0199	-0.184***
	(0.0138)	(0.0130)	(0.0239)	(0.0156)	(0.0126)	(0.0277)	(0.0208)	(0.0226)	(0.0342)
Instrument Relevance									
First Stage χ^2	19.20	10.02	9.25	12.28	3.98	8.53	12.67	10.60	3.22
p-value	0.000	0.002	0.002	0.000	0.046	0.003	0.000	0.001	0.073
Observations	1179010	567620	611390	709880	350169	359711	582495	268702	313793
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Panel A shows the results for outcome variable school–work status. Panel B shows the results for selection into employment types. Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

11 Figures

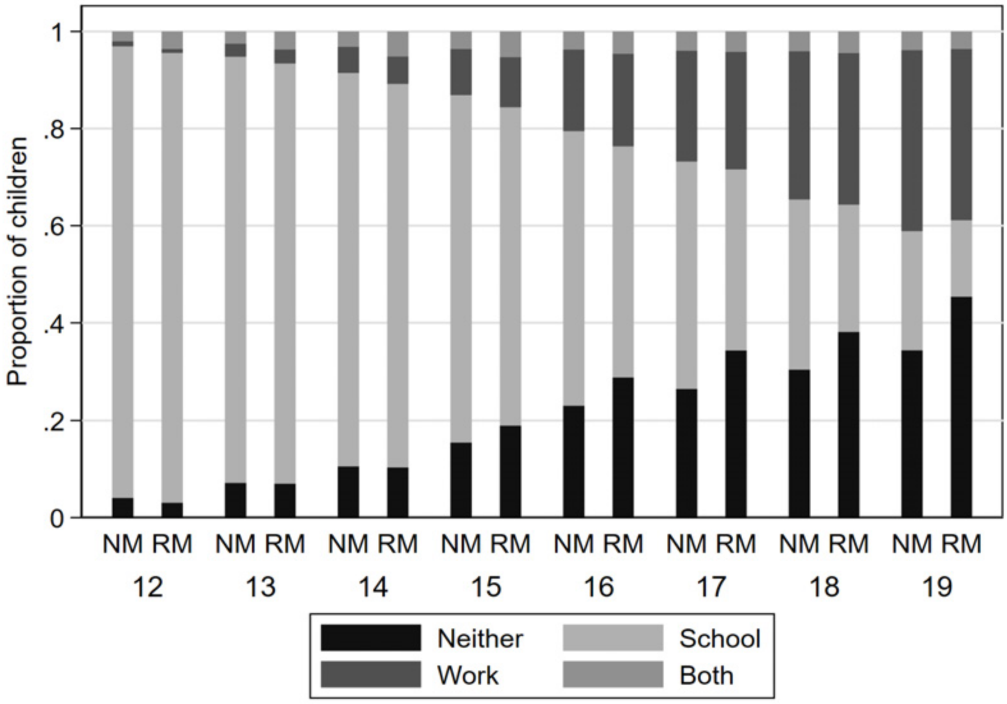
Figure 1: Mexican-born Immigrants in the United States (1960-2017)



Note: Data obtained from the Migration Policy Institute.

Figure 2: Outcomes by household return migration status and age

(a) School–Work Tradeoff



(b) Selection into Employment Types

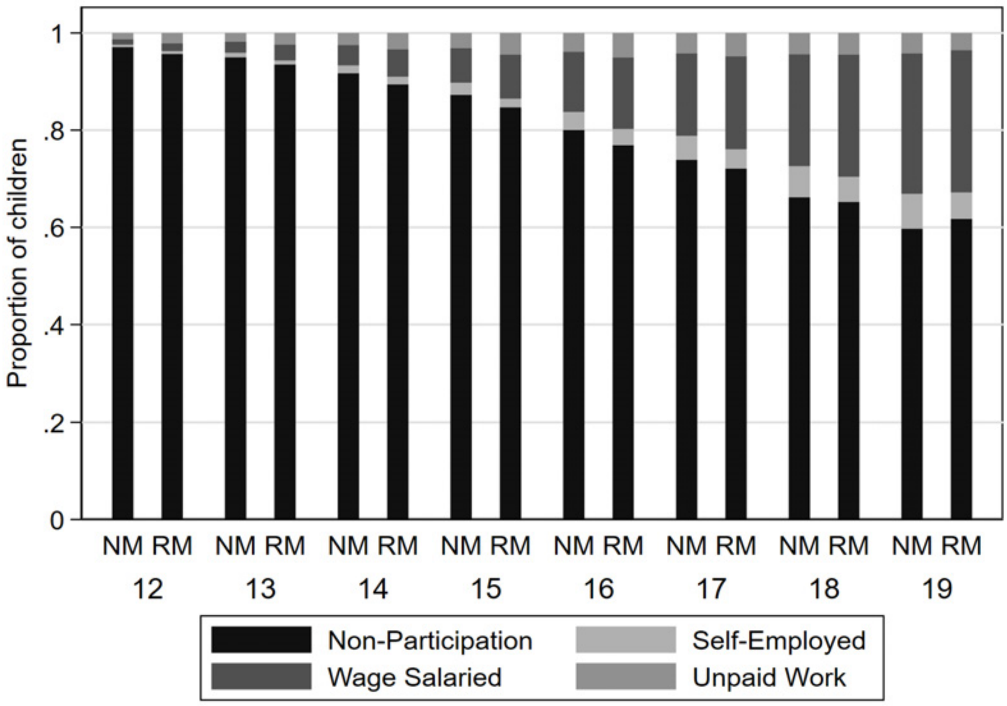
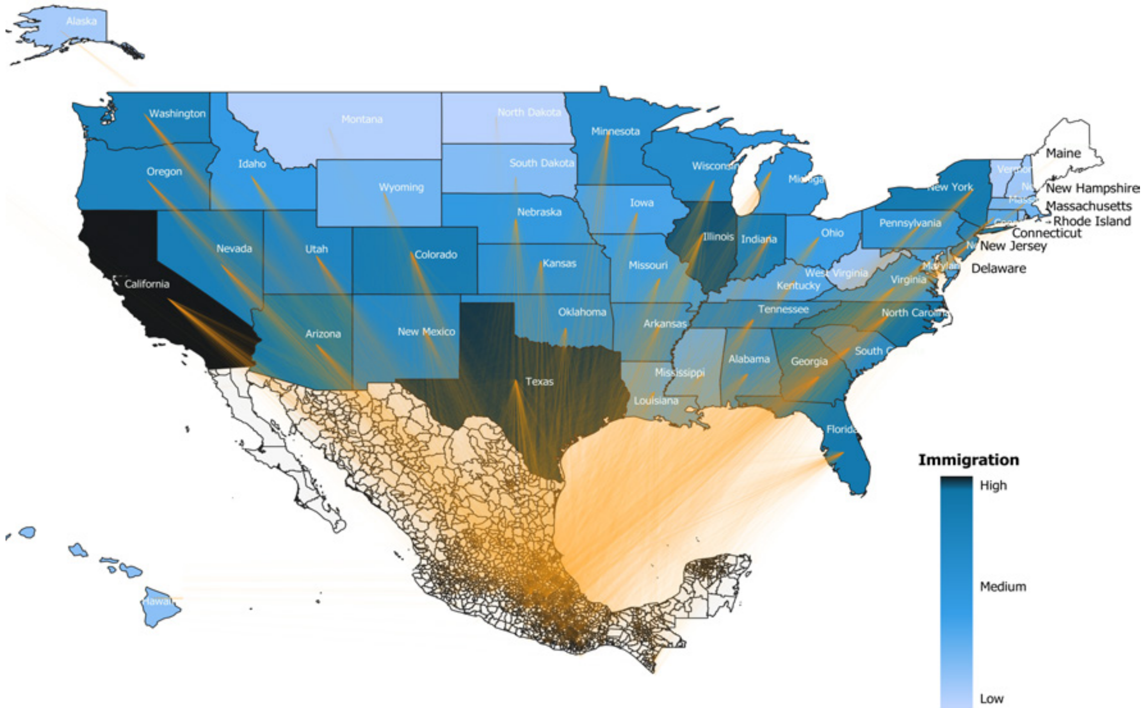


Figure 3: Map of migration flows from Mexican municipalities to U.S. states



Note: This map shows the migration links from Mexican municipalities to the states in the U.S. using 2008–2010 data of 2.3 million Mexican consular identification cards. Darker shades indicate the states with high rates of immigration from Mexico.

Figure 4: Exposure of Mexican municipalities to U.S. immigration enforcement

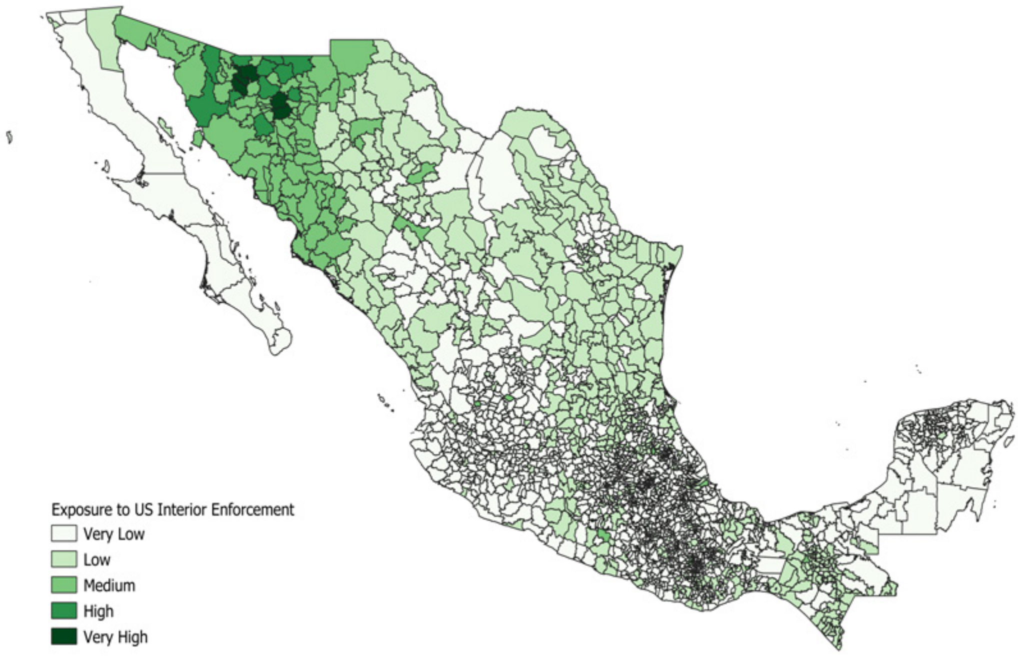
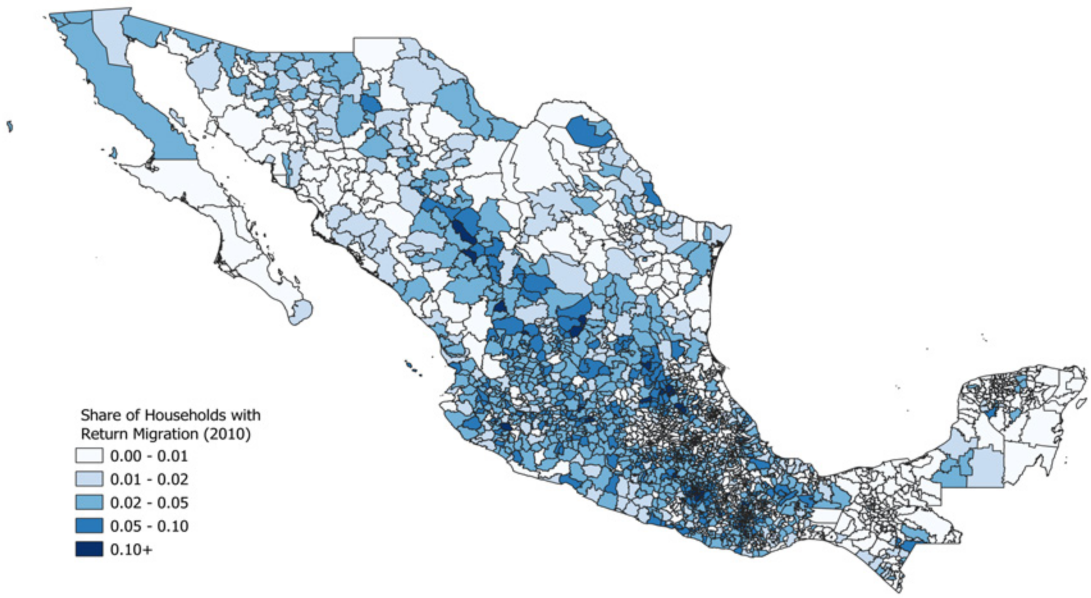
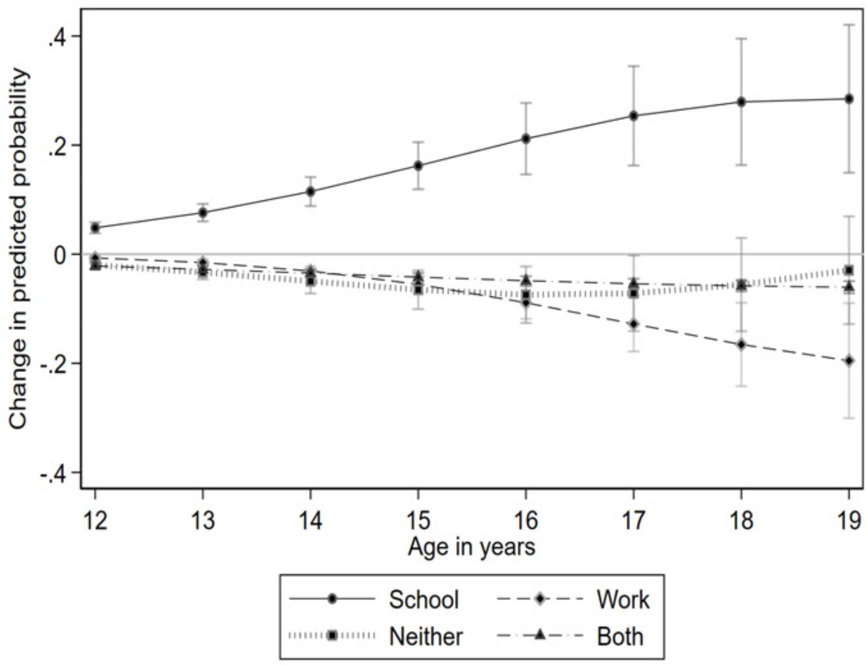


Figure 5: Share of households with return migrants in municipalities in Mexico



11.1 By Age

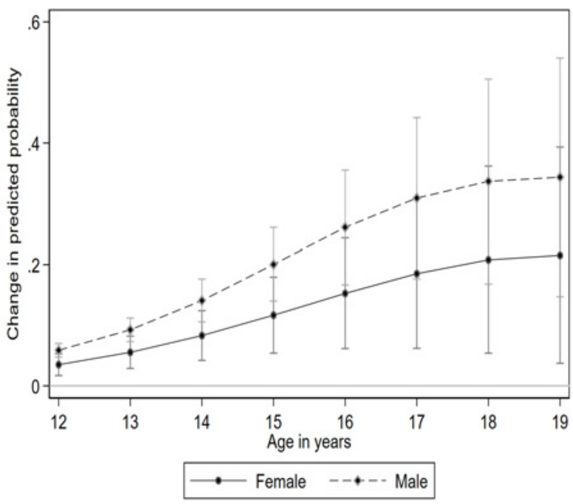
Figure 6: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Age



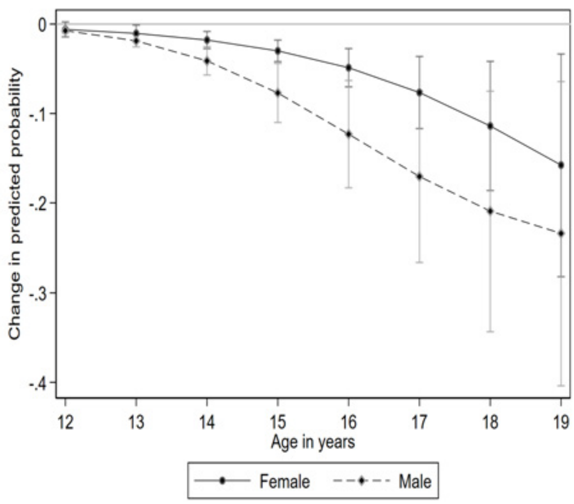
Note: The points represent the marginal effect of being in a return migrant household interacted by age for the entire sample. The bars extending from each point represent a 95 percent confidence interval of the standard errors.

Figure 7: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Age

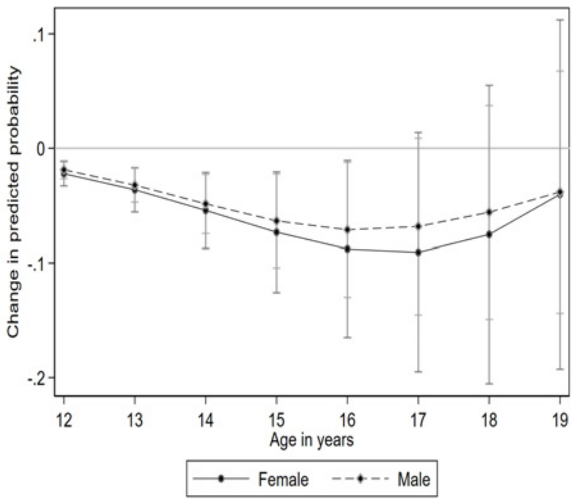
(a) School



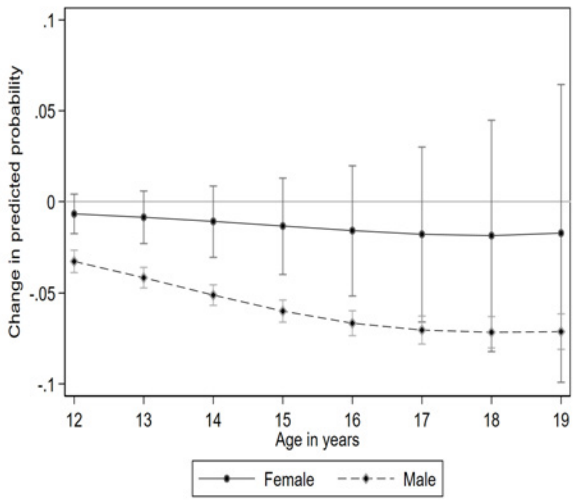
(b) Work



(c) Neither

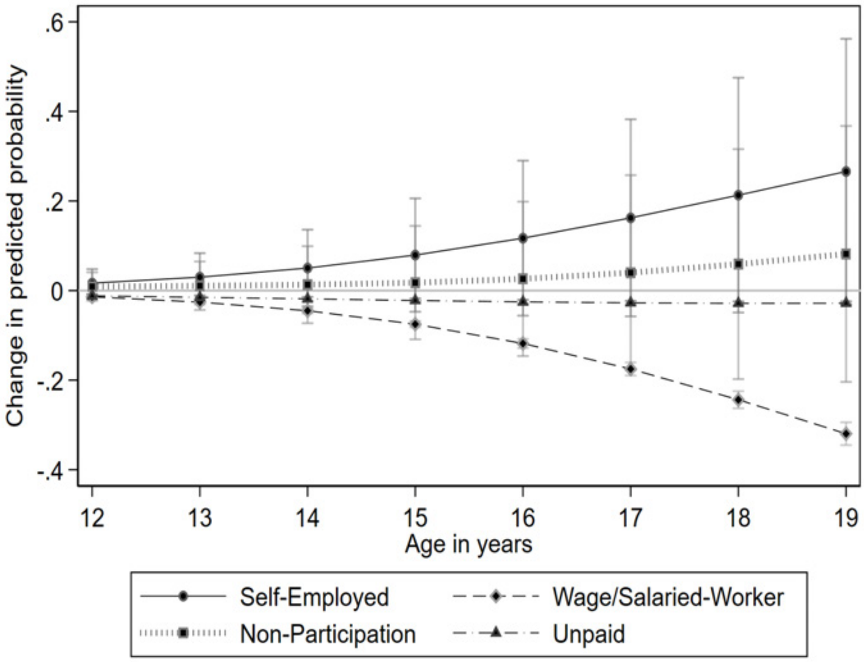


(d) Both



Note: The points represent the marginal effect of being in a return migrant household interacted by age, for male and female sample. The bars extending from each point represent a 95 percent confidence interval of the standard errors.

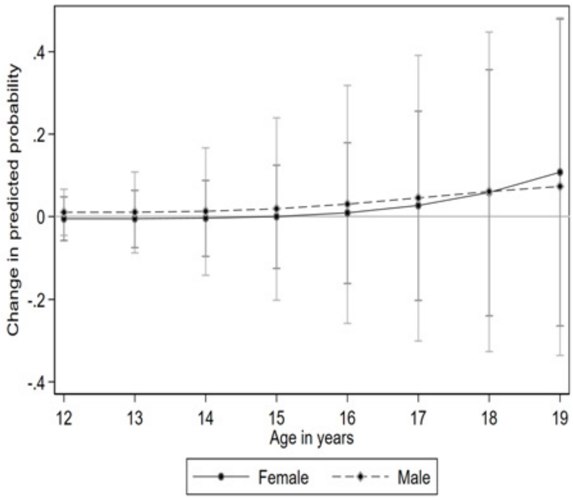
Figure 8: Average Marginal Effects of a Return Migrant in the Household on Selection into Employment Types by Age



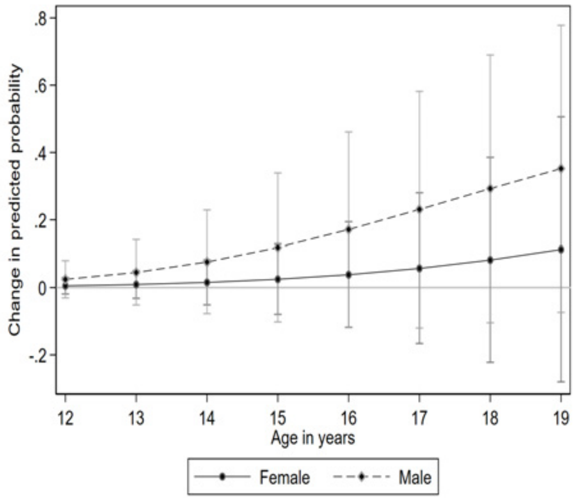
Note: The points represent the marginal effect of being in a return migrant household interacted by age for the entire sample. The bars extending from each point represent a 95 percent confidence interval of the standard errors.

Figure 9: Average Marginal Effects of a Return Migrant in the Household on Selection into Employment Types by Age

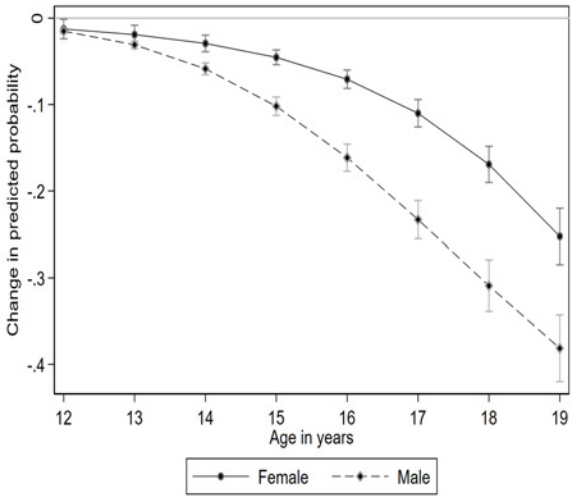
(a) Non-Participation



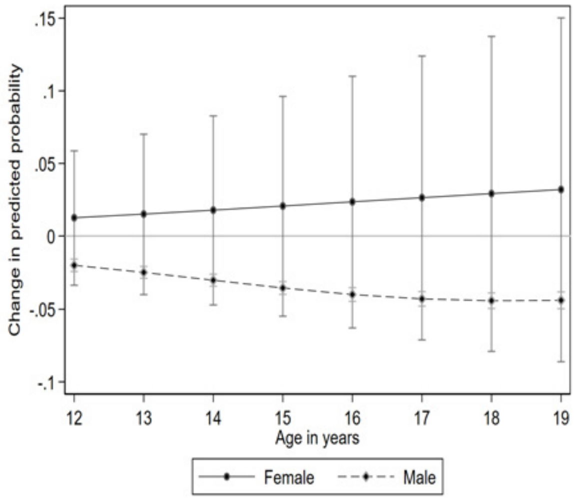
(b) Self-Employed



(c) Wage/Salaried Worker



(d) Unpaid Work



Note: The points represent the marginal effect of being in a return migrant household interacted by age, for male and female sample. The bars extending from each point represent a 95 percent confidence interval of the standard errors.

Figure 10: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Household Wealth

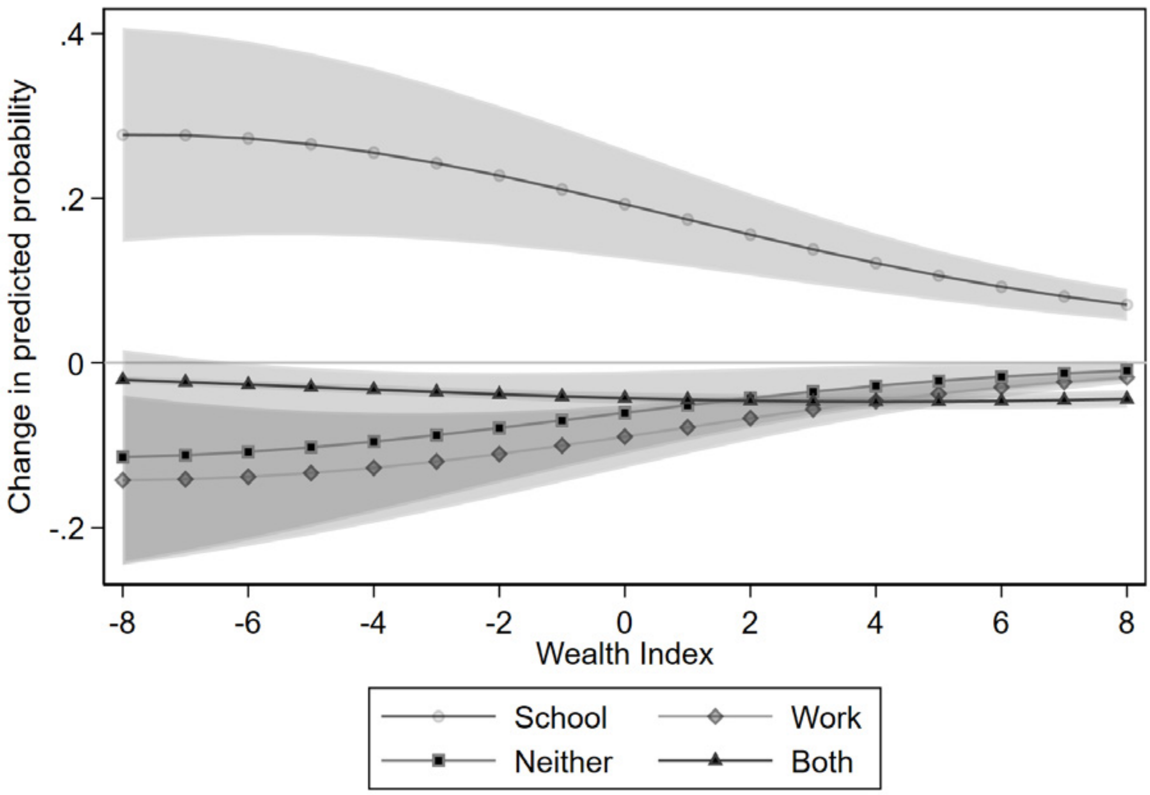
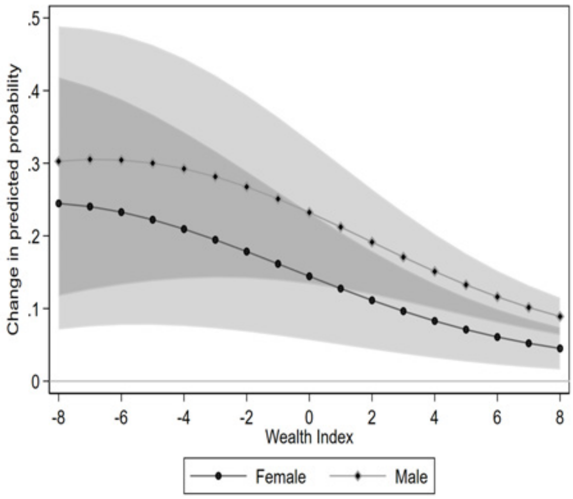
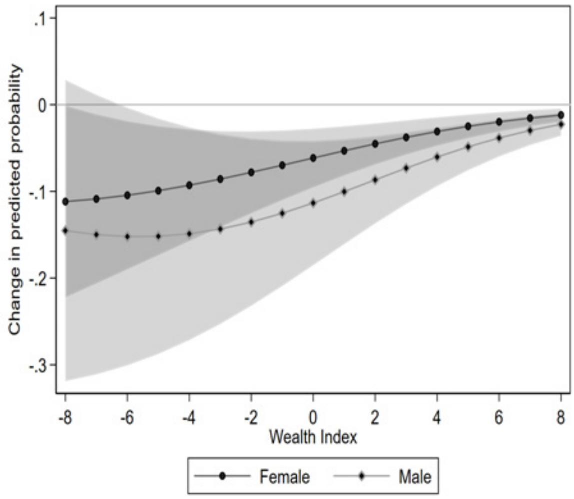


Figure 11: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Household Wealth

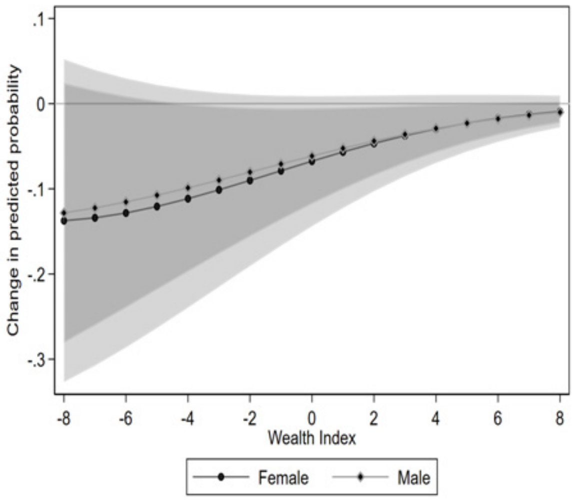
(a) School



(b) Work



(c) Neither



(d) Both

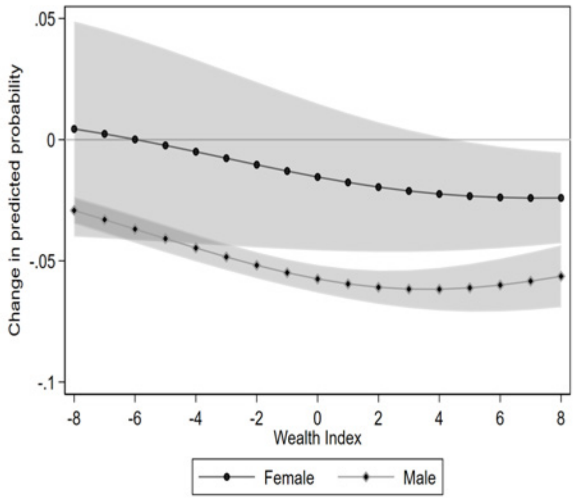
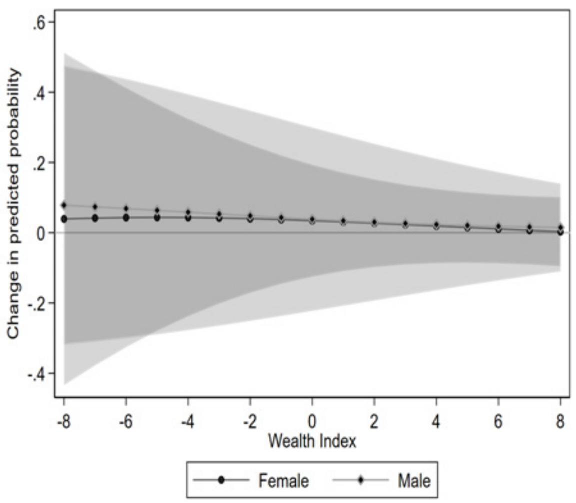


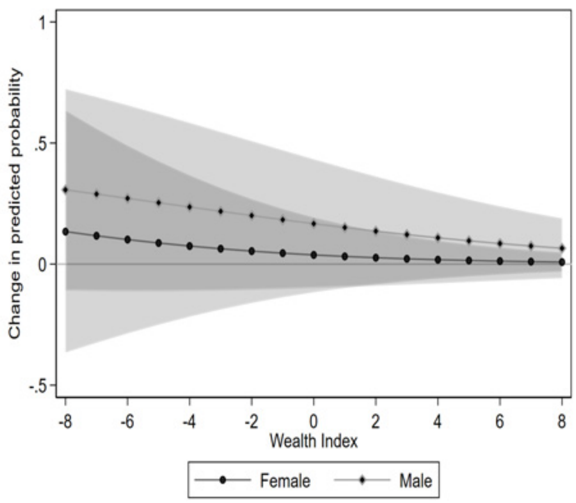
Figure 12: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Household Wealth

Figure 13: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff by Household Wealth

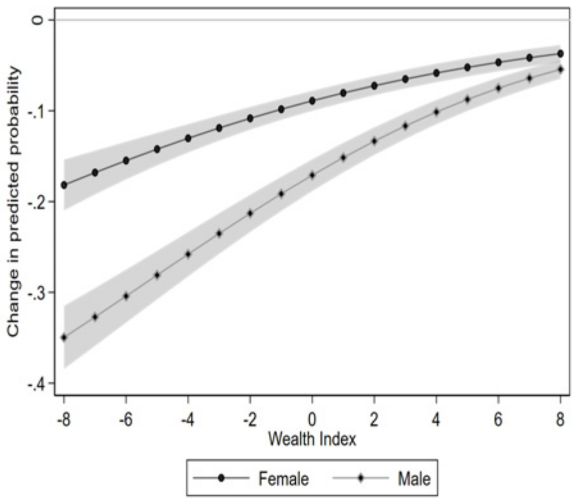
(a) Non-participation



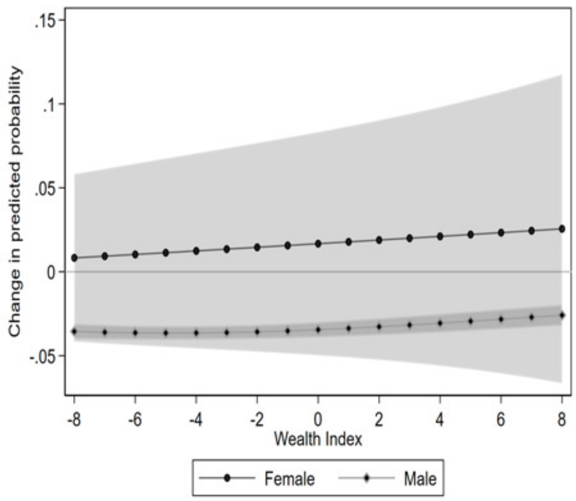
(b) Self-employed



(c) Wage/salaried work



(d) Unpaid work



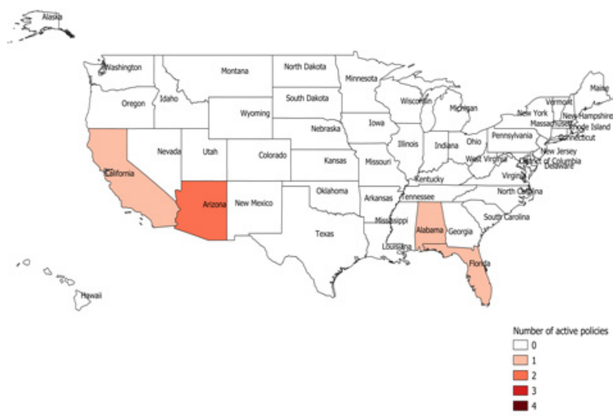
12 Appendix A

Table A.1: Detailed Data Source

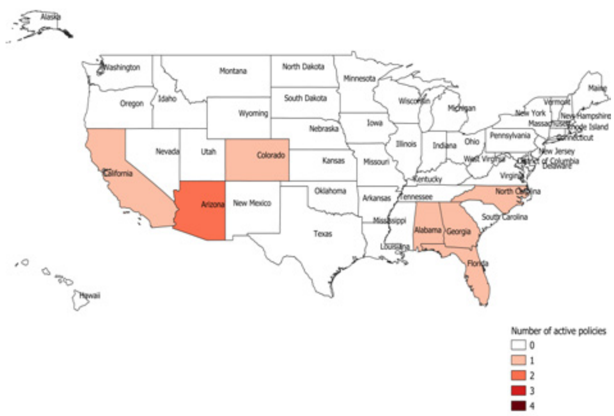
Variable Type	*Notes*	*Source*
Individual and Household characteristics	Collected from the Integrated Public Use Microdata Series (IPUMS) International database.	Mexican Census 2010
Mexican Municipality characteristics	Number of school per 1000 population, Average per capita income of Households, homicides, and expenditure	National Institute for Federalism and Municipal Development (INAFED) and National Institute of Statistics and Geography (INEGI)
Remittance	Percentage of households receiving remittances in a municipality	National Population Council (CONAPO)
US interior immigration enforcement	We collect information on four state-level immigrant and immigration policies status across U.S. states: The four policies we use are: a) 287(g) agreement; b) 287(g) jail agreement; c) Secure Communities program; d) E-Verify mandate.	Urban Institute

Figure A.1: Number of active immigration policy in U.S. from 2005–2010

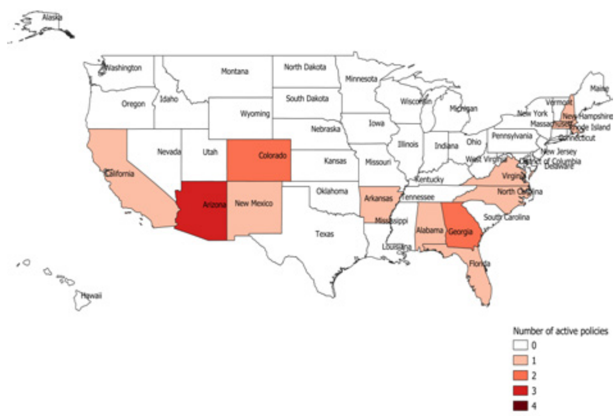
(a) 2005



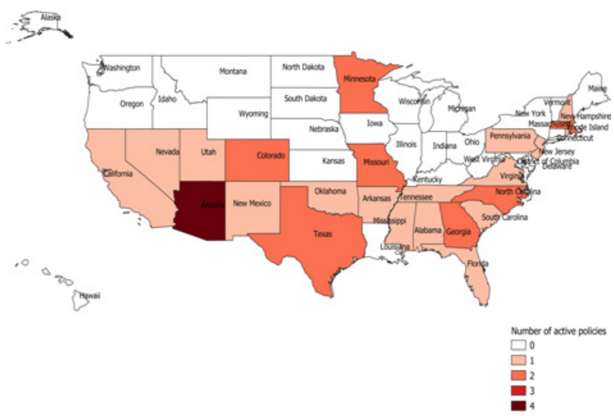
(b) 2006



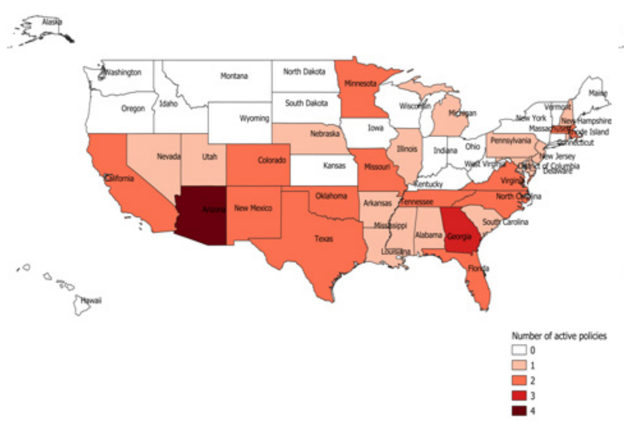
(c) 2007



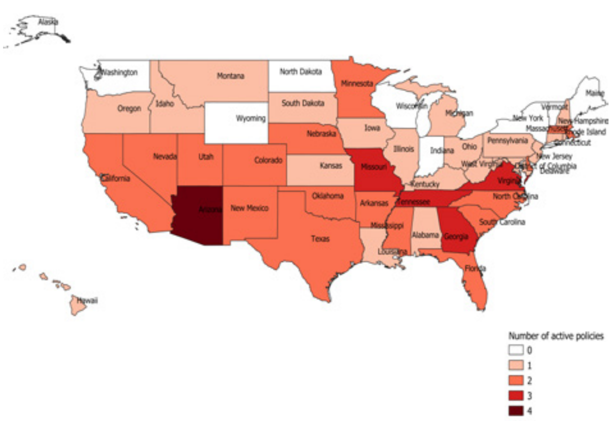
(d) 2008



(e) 2009



(f) 2010



Note: Data is from the Urban Institute State Immigration Policy Resource. In some states, few active policies were for counties with the most immigrants. However for ease of interpretation I have shown those states as fully implemented states.

Table A.2: Descriptive Statistics

	Mean	**SD**	**Min**	**Max**
	Panel A: Dependent Variable			
School Work Status				
Neither	0.148	0.355	0	1
School	0.678	0.467	0	1
Work	0.139	0.346	0	1
Both	0.035	0.183	0	1
Occupational Choice				
Non-Participation	0.826	0.379	0	1
Self-Employed	0.030	0.170	0	1
Wage Salaried	0.113	0.316	0	1
Unpaid Work	0.031	0.173	0	1
Hours worked per week	6.664	16.695	0	140
	Panel B: Independent Variable			
Age	15.243	2.221	12	19
Female	0.479	0.500	0	1
Mother's Hrs work/week	11.687	20.937	0	140
Num of own fam mem	5.940	2.265	2	36
HH wealth index	0.012	2.172	-7	7
Mother's Education				
$<$ *Primary*	0.408	0.491	0	1
P completed	0.476	0.499	0	1
S completed	0.086	0.280	0	1
U completed	0.030	0.171	0	1
Urban	0.500	0.500	0	1
% of HH Remittances (2010)	5.038	5.970	0	44
Ln(Income/percapita) (2010)	9.091	0.642	7	11
Number Homicide (2010)	41.222	237.574	0	3,766
Schools per 1000 people	3.600	2.469	1	18
Ln(Municip Expend) (2010)	18.384	1.563	14	23
Region				
North	0.147	0.354	0	1
Central	0.201	0.401	0	1
West	0.126	0.332	0	1
East	0.208	0.406	0	1
South	0.318	0.466	0	1
Observations	1292375			

Note: The table reports summary statistics for full sample with sample weights. Panel A shows the summary statistics for the dependent variables *Selection into Employment Types* and *school–work tradeoff*. Each dependent variable consist of four categories. Panel B shows the summary statistics for independent variables.

Table A.3: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff

	Full Sample	Female	Male
	(1)	(2)	(3)
Labor Outcomes			
Non-Participation	0.280***	0.162***	0.383***
	(0.0465)	(0.0534)	(0.0776)
Unemployed	-0.0149	-0.00377	-0.0317
	(0.0165)	(0.0184)	(0.0288)
Self-Employed	0.0524***	0.0203	0.0800***
	(0.0152)	(0.0181)	(0.0265)
Wage/Salaried Worker	-0.251***	-0.193***	-0.299***
	(0.0423)	(0.0490)	(0.0690)
Unpaid Worker	-0.0666***	0.0147	-0.133***
	(0.0129)	(0.0124)	(0.0223)
Observations	1287129	616663	670466

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Shock Test

	Interior Enforcement Intensity (2005-2010)
% of HH Remittances (2010)	-15.42***
	(-5.02)
Ln(Income/percapita) (2010)	0.141
	(1.00)
Number Homicide (2010)	-31.14
	(-0.94)
Schools per 1000 people	0.484
	(0.72)
Ln(Municip Expend) (2010)	0.359
	(0.98)

Note: The coefficients in this table were estimated separately by regressing the exogenous municipality-level controls from equations 6 and 8 on the instrumental variable (*immigration enforcement intensity*). All regressions include state fixed effects and standard errors are clustered at the municipality-level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

12.1 By Age Specification

Table A.5: Average Marginal Effects of a Return Migrant in the Household on School–Work tradeoff by Age

	Full Sample	Female	Male
	(1)	(2)	(3)
		School	
Age 12	0.048***	0.035***	0.059***
Age 13	0.076***	0.055***	0.093***
Age 14	0.115***	0.083***	0.141***
Age 15	0.162***	0.117***	0.200***
Age 16	0.212***	0.153***	0.261***
Age 17	0.254***	0.185***	0.309***
Age 18	0.279***	0.208***	0.337***
Age 19	0.285***	0.215**	0.344***
	(1)	(2)	(3)
		Work	
Age 12	-0.007***	-0.006	-0.007***
Age 13	-0.015***	-0.010**	-0.019***
Age 14	-0.031***	-0.018***	-0.041***
Age 15	-0.055***	-0.030***	-0.077***
Age 16	-0.089***	-0.049***	-0.123***
Age 17	-0.128***	-0.077***	-0.170***
Age 18	-0.166***	-0.114***	-0.209***
Age 19	-0.195***	-0.158**	-0.234***
	(1)	(2)	(3)
		Neither	
Age 12	-0.020***	-0.022***	-0.019***
Age 13	-0.033***	-0.036***	-0.032***
Age 14	-0.050***	-0.054***	-0.049***
Age 15	-0.065***	-0.073***	-0.063***
Age 16	-0.074***	-0.088**	-0.071**
Age 17	-0.072**	-0.091*	-0.068*
Age 18	-0.056	-0.075	-0.056
Age 19	-0.029	-0.040	-0.038
	(1)	(2)	(3)
		Both	
Age 12	-0.022***	-0.007	-0.033***
Age 13	-0.028***	-0.009	-0.042***
Age 14	-0.035***	-0.011	-0.051***
Age 15	-0.042***	-0.013	-0.060***
Age 16	-0.049***	-0.016	-0.067***
Age 17	-0.054***	-0.018	-0.070***
Age 18	-0.058***	-0.019	-0.072***
Age 19	-0.060***	-0.017	-0.071***
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6: Average Marginal Effects of a Return Migrant in the Household on Selection into Employment Types by Age

	Full Sample	Female	Male
	(1)	(2)	(3)
	Self-Employed		
Age 12	0.017	0.005	0.025
Age 13	0.030	0.009	0.045
Age 14	0.050	0.015	0.076
Age 15	0.079	0.025	0.119
Age 16	0.117	0.038	0.171
Age 17	0.162+	0.057	0.231
Age 18	0.213+	0.082	0.293+
Age 19	0.266*	0.113	0.352+
	(1)	(2)	(3)
	Wage Salaried		
Age 12	-0.014***	-0.013**	-0.015***
Age 13	-0.026***	-0.019***	-0.031***
Age 14	-0.045***	-0.029***	-0.059***
Age 15	-0.075***	-0.045***	-0.102***
Age 16	-0.118***	-0.071***	-0.161***
Age 17	-0.175***	-0.110***	-0.233***
Age 18	-0.244***	-0.169***	-0.309***
Age 19	-0.320***	-0.252***	-0.381***
	(1)	(2)	(3)
	Non-Participation		
Age 12	0.009	-0.005	0.010
Age 13	0.011	-0.005	0.011
Age 14	0.013	-0.004	0.013
Age 15	0.018	-0.000	0.019
Age 16	0.026	0.009	0.030
Age 17	0.040	0.027	0.045
Age 18	0.059	0.058	0.061
Age 19	0.082	0.108	0.073
	(1)	(2)	(3)
	Unpaid Work		
Age 12	-0.012***	0.013	-0.020***
Age 13	-0.015***	0.015	-0.025***
Age 14	-0.019***	0.018	-0.030***
Age 15	-0.022***	0.021	-0.035***
Age 16	-0.025***	0.024	-0.040***
Age 17	-0.027***	0.026	-0.043***
Age 18	-0.028***	0.029	-0.044***
Age 19	-0.028***	0.032	-0.044***
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

12.2 BiProbit

School–work tradeoff

I define S^* and W^* as the latent variables of attending school (S) and working (W), respectively.

$$S^*_{ihmr} = \alpha^S_1 RetMig_{ihmr} + \alpha^S_2 X_{ihmr} + \alpha^S_3 H_{hmr} + \alpha^S_4 M_{mr} + \alpha^S_5 \hat{\epsilon}_{ihmr} + \omega_r + e^S_{ihmr} \quad (10)$$

$$W^*_{ihmr} = \alpha^W_1 RetMig_{ihmr} + \alpha^W_2 X_{ihmr} + \alpha^W_3 H_{hmr} + \alpha^W_4 M_{mr} + \alpha^W_5 \hat{\epsilon}_{ihmr} + \omega_r + e^W_{ihmr} \quad (11)$$

where,

$$S_{ihmr} = \begin{cases} 1 & if \quad S^*_{ihmr} > 0 \\ 0 & if \quad S^*_{ihmr} \leq 0 \end{cases}$$

$$W_{ihmr} = \begin{cases} 1 & if \quad W^*_{ihmr} > 0 \\ 0 & if \quad W^*_{ihmr} \leq 0 \end{cases}$$

$RetMig_{ihmr}$ is a dummy variable indicating whether the household h in municipality m and region r where the child i lives have a return migrant. X_{ihmr} is a vector of individual characteristics, H_{hmr} is a vector of household characteristics, M_{mr} includes municipality-level controls, and e_r is region fixed effect. e^S_{ihmr} and e^W_{ihmr} are normally distributed error terms, with $cov(e^S_{ihmr}, e^w_{ihmr}) = \rho$.

In the traditional instrumental variable approach, the first-stage predicted value of return migration is placed in the second stage. However, due to the non-linearity of the Biprobit equation, it will not always provide a consistent estimate of α_1, the parameter of interest. To solve this problem, I use a control function approach which gives consistent estimates in this non-linear framework (Terza et al., 2008). In this approach, I include the first stage residual, $\hat{\mu}_{ihmr}$, as a control in the second stage.

Table A.7: Average Marginal Effects of a Return Migrant in the Household on School–Work Tradeoff

	Full Sample	Female	Male
	(1)	(2)	(3)
BIPROBIT: SCHOOL-WORK TRADEOFF			
School	0.195***	0.139**	0.239***
	(0.0466)	(0.0580)	(0.0723)
Work	-0.152***	-0.0767**	-0.207***
	(0.0303)	(0.0303)	(0.0542)
Neither	0.0239	-0.0309	0.0652+
	(0.0336)	(0.0491)	(0.0448)
Both	-0.0672***	-0.0316+	-0.0971***
	(0.0181)	(0.0210)	(0.0306)
Instrument Relevance			
χ^2	25.61	13.10	12.52
p-value	0.000	0.000	0.000
Observations	1291474	617458	674016
Controls	✓	✓	✓
Region FE	✓	✓	✓

Note: Robust standard errors in parentheses. All models control for individual, household and municipality characteristics, and region fixed effect described in the empirical section. All regressions include sample weights.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.