Paternal Migration and Educational Attainment in Rural Mexico

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Abstract

We examine the impact of international migration on educational attainment of migrants' children in rural communities using data from Mexican Migration Project (MMP143), with historical migration pattern and unemployment in popular destination as instruments. We find that if the father in a household has been a migrant worker, schooling of his children will be 1.3 years lower. This effect mostly comes from boys and older children, is smaller if parents have completed more years of education and/or migrated earlier in children's life. Our results provide support for two of the possible channels mentioned in the literature where migration could have reduced schooling: the brain drain channel and the family separation channel.

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1 Introduction

International migration from poor to rich countries has increased dramatically in the last two decades. A 2009 United Nations report[1] estimates the number of international migrants in the world in 2010 at 214 million, an increase of 35 million since 2000 and 58 million since 1990. One of the biggest migration flows of workers happens between Mexico and the United States. On the supply side, one in five households in rural Mexico has at least one member with international migration experience (McKenzie and Rapoport, 2011). On the demand side, Mexicans are by far the largest immigrant group in the U.S.: as much as 16 percent of Mexico's working age population is in the U.S. (Mishra, 2007).

Researchers presume, quite naturally, that migration improves first and foremost the economic livelihood of migrants themselves. As a result, until recently most research on migration, Borjas (1993) and Card (2001) for example, focused on outcomes for migrants themselves or the destination community. Evidence now suggests that migration has important consequences for the families and communities at the origin as well: education, medical expense, labor participation, among others[2]. In particular, tens of millions of children all over of the world are growing up with at least one parent living abroad. For example, Bryant (2005) estimates that 2 to 3 percent of Indonesian and Thai children have one parent working in a foreign country; an estimated 1.5 to 3 million Filipino children have a parent living abroad (Cortés, 2013). Data on Mexican migrants to the U.S. also reveal that a substantial number of male heads of household with families in Mexico leave at least one minor child at home (Antman, 2012b). These facts have brought new-found attention to the consequences of these separations for the educational outcomes of the children of migrants. Since origin countries are typically part of the developing world, these studies have particular importance because they coincide with the interest in economic development more broadly. The direction and magnitude of these effects, though increasingly investigated, are not yet fully understood.

The current study examines the impact of father's migration on educational attainment of migrants' children in rural Mexico. The general impact is unclear theoretically, since migration can affect children's schooling in many ways. For instance, remittance can ease the credit constraint in human capital investment, but family

[1] See *International Migration Report 2009: A Global Assessment*, available at `http://www.un.org/esa/population/publications/migration/WorldMigrationReport2009.pdf`.

[2] For a review of the literature, see Antman (2012c).

separation resulted from father's absence could have a detrimental effect on children's development. These different and opposite channels leave this question an empirical one. Estimation of the general effect is made harder by the endogeneity problem between migration and education: households with migrants may share some hidden characteristics with households with high (or low) educational attainment. Besides, the exact mechanism of this impact has not been thoroughly studied. We follow McKenzie and Rapoport (2011) and Antman (2011a) in using historical migration rate and unemployment at popular destinations as instrumental variables to treat the endogeneity problem and identify the general impact.

We focus on the rural population (as opposed to both urban and rural data in Antman (2011a)) for two reasons. First, in urban areas whole-family migration is more prevalent, which leads to selection bias in the sample. Second, the distribution of education, and hence the distribution of the hidden characteristics, are likely to be different between urban and rural areas. We also limit our attention to migrant fathers, since number of working mothers is small in a rural setting, let alone migrant mothers. Our main instrument of interest is unemployment rate at popular destinations, which varies at community level, comparing to historical migration rate which varies at state level. This allows us to capture the effect as the result of comparing communities where migration is prevalent with other communities, while McKenzie and Rapoport (2011) only captures this effect as the result of state-level variation. Then, we extend the basic IV regression, introducing household and timing heterogeneity into the model, and discuss the relative importance of various channels based on the results.

The rest of this paper is organized as follows: Section 2 describes the different channels through which migration can affect educational attainment and related literature; Section 3 describes the econometric model and instruments used; Section 4 provides basic information and descriptive statistics of the data; Section 5 presents the OLS and IV regression results; Section 6 explores the different channels by looking at heterogeneity in the effect of migration; Section 7 concludes the paper.

2 Migration and Education: the Channels

There are many channels through which parent's migration can affect children's education. In theory, the signs of these impacts are different, so estimating the

general effect empirically is not trivial. Most of the literature has been focusing on this general effect without discerning the possible channels. Hanson and Woodruff (2003) and McKenzie and Rapoport (2011) both use historical pattern in Mexico-US migration as instrument for migrant presence (all adult migrants, instead of just the parents) in the household. The former finds a positive effect for younger children; the latter finds a negative one for all children in rural areas. Antman (2011b) uses employment statistics at destination as an IV and manage to find negative effect on time spent in studying for children aged 12-15 in an urban Mexican data set. Using similar instruments, Miranda (2011) finds a negative effect of migration on children's high school graduation rate, with larger impact for older children and children in more affluent households. In another study, Antman (2012b) studies both urban and rural sample in Mexican Migration Project; she identifies the timing of migration in order to set up a difference-in-difference regression, with family fixed effects. The results suggest that paternal U.S. migration during children's school years has a positive effect on younger girls.

Some recent works actively identify and estimate the effect of possible routes separately. The following is a list of possible routes suggested in the literature. A summary of the different channels and effects is in Table 1.

First, remittances relax resource constraints within household, allowing more investment in education. If this is the main channel, we expect to see positive impact on children's educational attainment, more so if the working period is longer. This is by far the most studied channel in the relationship between migration and education due to the relative ease in obtaining data. One of the earlier papers is Cox Edwards and Ureta (2003), which uses a hazard model to study the effect of war-driven migration on school retention in El Salvador; they find a positive effect without explicitly treating the endogeneity between migration and education. Since then, various studies look at the effect of remittance on education in South America, including Acosta (2011) on El Salvador, Adams Jr. and Cuecuecha (2010) on Guatemala, Calero et al. (2009) on Ecuador, and Borraz (2005) on Mexico. Studying the case in Asia, Yang (2008) relies on variation in exchange rate to estimate the effect of remittances in the Philippines. He shows that larger amounts of remittances do result in an increase in children's schooling.

Second, the migration of parent(s) leads to family separation which could have negative consequences for children. This effect is likely to be larger the longer the migration spell is. Since the migrant we look at currently is the father, we expect to

see larger negative impacts for boys than for girls. The impact is likely to be larger if the child is young and if the length of absence is long. Studying the case in the Philippines, Cortés (2013) uses families with migrant fathers as control to show that mother's absence has a greater detrimental effect on children's education.

Third, possibility of working abroad can either encourage or discourage education, depending on the relative return of education. This effect is known as brain drain/brain gain in the literature (Beine et al., 2008, 2010; Mountford, 1997; Docquier and Rapoport, 2012). Chiquiar and Hanson (2005) have shown that the return to Mexican education is lower in the U.S. than in Mexico, so in our case a brain-drain effect is more likely. The mechanism could be the following: migrant workers and their family members back home will gain more information about return to education in the U.S. over time, so the brain-drain effect is likely to be larger if the migrants spend more time in the U.S and if the child is older. Again, since the migrant is male, the effect should be larger for boys. There have been anecdotal and descriptive statistic reports on such an effect (Battistella and Conaco, 1998; Kandel and Kao, 2000, 2001). Beine et al. (2010) points out, however, that brain drain/brain gain estimates could be very unreliable.

Finally, with father being abroad, mother assumes more power in family decision making, including but not limit to resource allocation. There has been literature, Duflo (2003) among others, suggesting that investment on children's - especially girls' - education increases when women have more power in distribution household income. If this is one of the main channels, we expect to see positive effects in general and a larger effect if the child is female and if father has been away for a long time. Antman (2012b) has some discussion on this front.

In this paper, we attempt to first look at the general effect, and then assess the importance of the different channels by introducing household and timing heterogeneity into the basic model.

3 Econometric Model

We are interested in the general effect β of living in a household with a migrant father on educational attainment:

$$Schooling_i = \beta Migrant_i + \gamma X_i + \varepsilon_i$$

where $Schooling_i$ is educational attainment for a child measured in years of schooling completed, $Migrant_i$ is a dummy variable signifying whether the father in a household has ever been a migrant, and X_i is a set of controls regarding personal, family, and community characteristics.

Even if father last migrated before the child starts schooling or before the child is born, $Migrant_i$ could still affect educational attainment through different channels, including remittance and brain-drain.

The key problem in estimating this model is potential endogeneity in $Migrant_i$: $E\left[Migrant_i \cdot \varepsilon_i\right] \neq 0$, i.e. the same (unobserved) characteristics could have effects on both migration status and educational attainment[3]. One possible way to address this problem is to use a set of instrumental variables Z_i, that satisfies $E\left[Z_i \varepsilon_i\right] = 0$, for migrant status $Migrant_i$.

A candidate instrument for migrant status is historical migration rate. Existing migration network lowers the cost for future migrants, so they are more likely to move to places where many local predecessors have gone (Hanson and Woodruff, 2003; McKenzie and Rapoport, 2007). However, historical migration rates are partly determined by social-economic factors like historical inequality and development level, which probably still influence current economic and education outcomes (McKenzie and Rapoport, 2011). We can alleviate the problem by controlling for some historical variables and/or interact historical rates with current characteristics. For this study we collect Mexican migration population in the U.S. in 1924 at the Mexican state level from Foerster (1925). To address the endogeneity problem of this instrument, we control for proportion of rural households owning land by state in 1910 Mexico taken from Mcbride (1923), a measure of inequality and economic development.

Looking at the demand side of migration, we can map Mexican communities into U.S. destinations by observing the current migration pattern, and then use employment situation at the destination as an instrument (Antman, 2012a). As a feature on the demand side, it is likely to have influence on the decision of potential migrant workers; since this is a U.S.-based variable, it is relatively unlikely to correlate with unobserved characteristics in Mexico households. We use MMP143 to identify the U.S. cities which are most likely to be the most recent migration destinations for the migrants from a Mexican community; for a summary of this connection see Table 2. Then we link observations with unemployment data of the year the community is

[3]See McKenzie et al. (2010) for a discussion on possible endogeneity in migration status.

surveyed from the Bureau of Labor Statistics according to the said correspondence. This is a relevant instrumental variable - at least for non-migration - as when the unemployment rate in the destination is high, fathers who have never been to the U.S. is unlikely to go.

One concern is that since all the instruments are from community level and above, they may reflect regional difference other than migration prospects. We argue that workers from all over Mexico do go to a few popular destinations like Chicago and Los Angeles, so our instruments are not merely picking up regional fixed effects; see Figure 2 for an illustration. Another possible concern is the correlation between U.S. and Mexican business cycles , leading to endogeneity of unemployment rates in the U.S. To address this concern, we control for household income as a proxy of Mexican economic performance in most specifications.

The errors ε_i could be correlated within communities so we implement the two-step efficient generalized method of moments (GMM) estimator[4] in estimating the model and report standard errors clustered at community level in the regression results.

Our ultimate goal is to discern the main channels through which migration affects education, while this model estimates only the average treatment effect of migration on schooling. To look at heterogeneity in treatment effect, we further our investigation by interacting migration status with family-specific characteristics W_i:

$$Schooling_i = \beta Migrant_i + \delta Migrant_i \cdot W_i + \gamma_w W_i + \gamma_x X_i + \varepsilon_i$$

We can infer possible channels by studying how different family characteristics change the treatment effect of migration on children's education.

4 Data

The Mexican Migration Project (MMP), available at `mmp.opr.princeton.edu`, is a collaborative research project by Princeton University and the University of Guadalajara. It started collecting migration-related data in a few communities in 1982 and continues to do so every year since 1987. As of the last update (MMP143 in 2013), it has data for 143 communities. Each year, during the winter months (when seasonal

[4]See Davidson and MacKinnon (2004), pp 362-365.

migrants tend to return home), the MMP randomly samples households in communities located throughout Mexico. After gathering social, demographic, and economic information on the household and its members, interviewers collect basic immigration information on each person's first and last trip to the United States. Following completion of the Mexican surveys, interviewers travel to destination areas in the United States to administer identical questionnaires to migrants from the same communities sampled in Mexico who have settled north of the border and no longer return home. These surveys are then combined with those conducted in Mexico. Massey and Zenteno (2000) argue that MMP is a reasonably accurate profile of rural Mexican migrants to the United States; in recent years it covers more and more urban communities as well. Though this data set is not a national representative sample, misrepresentation of a certain group should not be an issue since our goal is to find the causal relationship between migration and educational attainment (Solon et al., 2013).

As primary education coverage is almost universal in Mexico (Santibañez et al., 2005), we focus on the impact on secondary-aged children of the migrants. Our sample includes all children aged 11-19 living in a rural (defined as a community with a population of less than 50000 people) area post-1997[5]. For a map of all states represented in the sample, see Figure 1.

These children are likely to have finished or about to finish primary school but not all of them are in the job market. We pick a rural sub-sample from MMP143 because we believe the channels could be different for urban and rural households, and urban migrants are more likely to take family members with them (McKenzie and Rapoport, 2011). We focus on international migrations and define the father[6] in a household as a migrant if he has reported migrant trips to U.S. and Canada in or before the survey year.

Table 3 shows some basic descriptive statistics of the sample. Children with migrant fathers on average are younger, have completed slightly fewer years of schooling (but comparable to the age difference), live in smaller households, and more likely to be girls. None of these differences are statistically significant. In Figure 3 we notice that the distributions of educational attainment do not differ much between migrants' children and non-migrants' children.

Migrant fathers usually have finished fewer years of education, but because of

[5]The measurement of household income in MMP143 is different pre- and post- 1997.

[6]We do not look at migrant mothers as most of the migrants are men, and the ratio of working mothers and migrant mothers is very low (about 30% and 5% respectively) in the rural sample.

working abroad they have a higher income. The migrant ratio is exceptionally large (about one-third) in the sample, given that migrant and non-migrant households have roughly the same number of children.

5 General Effects

5.1 OLS and IV Regression Results

We first examine the impact of father being a migrant on children's years of education completed. The control variables include age, age squared, gender and birth order of the child; father's and mother's years of schooling completed, family size and income; and number of secondary schools per 1000 residents in the *Municipio.* Table 5 shows the results from OLS regression and IV regression, each reporting standard errors clustered at the community level under two specifications, one with household income controls and one without[7].

OLS regressions show little and insignificant consequences from father being a migrant. Most other controls, including parents' education and number of children in the household, have expected effects. Interestingly, girls finish significantly more years of education than boys, holding everything else constant.

To account for the endogenous effect in migrant status, we use historical migration and destination unemployment as instruments. Table 4 shows the first-stage results using these instruments. For the main IV regression, we employ two-step GMM IV regression[8] in Stata 11. We reject the null of weak instruments in Stock and Yogo (2002) test, and fail to reject the null in over-identification test for all IV specifications in our full sample.

The results, shown in Table 5, suggest that living in a household with a migrant father can reduce children's educational attainment by about 1.3 years, and the results are significant at 5% level. This result has the same sign as McKenzie and Rapoport (2011) - but slightly larger effect - and opposite to Hanson and Woodruff (2003). Given that the average years of education completed for the sample is less than 8 years, paternal migration seems to have a large negative impact. Moreover, if people migrate more due to a lower unemployment rate, earnings and

[7]Household income data is missing for about one-third of children in the sample.
[8]Applying `ivreg2` package by Baum et al. (2010)

remittances should be higher. As a result, the remittance effect ought to raise children's education. On the contrary, we found a general negative effect, which either suggests that the true effect of migration is even stronger, or remittance is not as important a channel in influencing educational attainment. Compared to the OLS results, the IV result also hints at positive selection in migration. Since all instruments are on community level and above, this may reflect more about local custom than the act of migration itself: people in communities with long migration tradition and good current migration prospect are less likely to invest a lot in education; they may want their children to end schooling early and test their earning potential in the U.S. This is most akin to the brain-drain channel mentioned above: the next generation is expected to work in the U.S. where return to Mexican schooling is lower, so education investment is not a big concern for families in these communities. The negative overall effect implies family separation could play a key role as well.

Our next exercise is to divide our sample into four gender-age groups and see how the effect of migration varies among them. The result is shown in Table 6. Most children do not go to school any more after age 16, as manifested by the insignificant effect of age for children older than 16. The negative effect of paternal migration is significant for boys and older girls, and is larger for older children. The effect on younger girls is insignificant. Difference between age-gender groups lends support to the family separation channel, where boys would react more drastically than girls in case of a paternal absence; and the brain-drain channel, where boys and older children are more likely to be informed of education return in the U.S. and drop out of school accordingly.

5.2 Robustness Checks

The results are robust to restricting sample to children aged 12-18 and 13-17. If we define rural communities as one with a population with less than 10000 residents instead of 50000, then the sign and magnitude of the results still hold, but the exact effect cannot be identified accurately, partly due to the smaller sample size[9]. Also, results are robust to using instead age and birth order order dummies as controls.

A potential concern about using years of schooling as the outcome variable is that it is right-censored in the sense that the data collector do not know whether the in-

[9] About one-third of the observations are in communities with 10000-50000 residents

terviewee will have more years of education after the interview is done. To address this concern, we conduct a probit estimation:

$$Lag_i = \beta Migrant_i + \gamma X_i + \varepsilon_i$$

where Lag_i is defined as whether age minus schooling is larger than 8; assuming the latest "normal" age to attend school is 8, if $Lag_i = 1$ then child i is likely to be either lagging behind in terms of school years or have dropped out altogether.

The probit and IV-probit results are reported in Table 7. The results agree with our previous estimations: living in a household with a migrant father increases children's chance of lagging behind or dropping out of school. The effect on the average children is more than 20%, supporting the large negative impact of paternal migration.

6 Heterogeneous Effects and Likely Channels

6.1 Socioeconomic Factors

To gain information on the possible channels, it is useful to look at how different family characteristics affect the treatment effect of migration. We start by interacting household income and parents' educational attainment with father's migration status. The four channels we identified in Part 2 are likely to put forward different changes in the effect as the household income and education level changes. Remittance channel and maternal empowerment channel work through allocating more income to education, so a larger negative total effect is expected for high income/education households for they are less likely to be limited from the beginning. With more resource available, educated and affluent families are able to cope with family separation from paternal absence better, and are less likely to consider low-wage employment to the U.S. As a result, we shall see a smaller negative impact.

The results are shown in Table 8. Significant coefficients on parents' educational attainment imply that the negative impact of migration on children's schooling is smaller in families with highly-educated parents. Having about 8 years of schooling for either father or mother is enough to turn the effect of migration into a positive one. We also estimate the original model but with sub-samples divided

according to parents' education. The results in Table 9 exhibit the same general outcome: children in families with educated parents suffer less from father's migration. Based on the discussion above, Tables 8 and 9 lend support to the family separation channel and the brain drain channel. Interestingly, the interaction from family income level is insignificant in both specifications.

We then divide the sample by gender and examine the effects. In Table 10 we can see that the heterogeneous effect of education is larger if it comes from the same-sex parent even when only father's migration is being studied, which could be the result of different role-models within family. One possible explanation for boys is that they indeed follow father's footstep and plan to abandon schooling in favor of an early migration.

6.2 Timing of Migration

Finally we study how the effect changes according to the timing of migration. Before the child is born, the more likely channel is remittance, which could have ease the credit constraint for the years to come; after childbirth, all four channels are possible, with family separation and maternal empowerment being most sensitive to the timing of migration. Father leaving for the U.S. before his child is born will have very different effect from a father leaving for the U.S. when his child is in secondary school.

This intuition is supported by results shown in Table 11: if father left the children recently, the negative impact could be over three times the general impact of migration. Comparing the general effect and the effect when migration happens after childbirth, we can see that the effect of a migration trip before childbirth is almost zero. One interpretation of this result is that father's absence plays an important role in the impact of migration on children's education: if father migrates when the child is attending school, the separation of family cripples child's ability to develop and study in school, so the child is unable to finish more years of schooling. Another possibility is that if the father migrates when the child has already finished primary education, the child is likely to feel the need of supporting the family while father is away, thus stops attending school and takes up a job.

7 Conclusion

Equipped with MMP143 data set and two instruments, we find that in rural Mexico, if the father in a household has been an international migrant worker, schooling of his children will decrease by about 1.3 years, and the effect is larger for boys than for girls. The results are larger than that in the previous literature (less than 1 year overall in McKenzie and Rapoport (2011)). The discrepancy could be a result from the different instruments used. Because of the limitation of the instruments, this is more likely a result of local custom instead of personal act. To measure the impact due to migrant father in a particular family, we need an instrument that varies at the household level, or use a panel data and exploit the family fixed effect.

The gender-age group results show that the effect mainly comes from boys in the sample. This fits in the story in Antman (2012b) among others, but the total effect is different; while Antman (2012b) finds positive impact for girls, our data show no significant effects for younger girls and negative effect for older girls. This may be due to the difference in the sample: while Antman (2012b) uses the full MMP sample with both urban and rural children, we focus on rural data, for the mechanism of migration could be different between urban and rural residents. According to the results measuring heterogeneity in migration effects, the negative impact could be smaller or even eliminated if parents have a high level of schooling and/or father migrates before the child's school years. The heterogeneity exercise also suggest that remittance may not be as important as previously suggested in the literature; rather, the other channels should receive more attention in further investigation.

In sum, we find evidence that father's migration has a negative and significant effect on children's educational attainment, which mainly comes from the family separation channel and the brain drain channel. In other words, children in migrant families first took a hit in family structure when the father migrated; when children are close to working age, father's experience abroad encourages them to find a job instead of continuing schooling.

There are a number of ways that possible future studies can be conducted. For example, educational attainment measured in teenage children is right-censored as some of them may not have finished schooling. A full maximum-likelihood model addressing this issue is likely to obtain more accurate results. Improvements could also be made regarding the measurement of schooling, since school quality varies

a lot across Mexico (Palafox et al., 1994) and other developing countries (Schoellman, 2012). Incorporating difference in school quality in different communities can show us a better picture of educational attainment for children in migrant families.

References

Acosta, P. (2011). School Attendance, Child Labour, and Remittances from International Migration in El Salvador. *Journal of Development Studies*, 47(6):913–936.

Adams Jr., R. H. and Cuecuecha, A. (2010). Remittances, Household Expenditure and Investment in Guatemala. *World Development*, 38(11):1626–1641.

Antman, F. M. (2011a). International Migration and Gender Discrimination among Children Left Behind. *The American Economic Review*, 101(3):645–649.

Antman, F. M. (2011b). The Intergenerational Effects of Paternal Migration on Schooling and Work: What Can We Learn from Children's Time Allocations? *Journal of Development Economics*, 96(2):200–208.

Antman, F. M. (2012a). Elderly Care and Intrafamily Resource Allocation when Children Migrate. *The Journal of Human Resources*, 47(2):331–363.

Antman, F. M. (2012b). Gender, Educational Attainment, and the Impact of Parental Migration on Children Left Behind. *Journal of Population Economics*, 25(4):1187–1214.

Antman, F. M. (2012c). The Impact of Migration on Family Left Behind. *IZA Discussion Paper*, 6374.

Battistella, G. and Conaco, M. C. G. (1998). The Impact of Labour Migration on the Children Left Behind: A Study of Elementary School Children in the Philippines. *SOJOURN: Journal of Social Issues in Southeast Asia*, 13(2):220–241.

Baum, C. F., Schaffer, M. E., and Stillman, S. (2010). ivreg2: Stata Module for Extended Instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class Regression.

Beine, M., Docquier, F., and Rapoport, H. (2008). Brain Drain and Human Capital Formation in Developing Countries: Winners and Losers. *The Economic Journal*, 118(April):631–652.

Beine, M., Docquier, F., and Rapoport, H. (2010). On the Robustness of Brain Gain Estimates. *Annals of Economics and Statistics*, 97-98:143–165.

Borjas, G. J. (1993). The Intergenerational Mobility of Immigrants. *Journal of Labor Economics*, 11(1):113–135.

Borraz, F. (2005). Assessing the Impact of Remittances on Schooling: The Mexican Experience. *Global Economy Journal*, 5(1).

Bryant, J. (2005). Children of International Migrants in Indonesia, Thailand, and the Philippines: A review of evidence and policies. *Innocenti Working Paper*, 2005-05.

Calero, C., Bedi, A. S., and Sparrow, R. (2009). Remittances, Liquidity Constraints and Human Capital Investments in Ecuador. *World Development*, 37(6):1143–1154.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, 19(1):22–64.

Chiquiar, D. and Hanson, G. H. (2005). International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States. *Journal of Political Economy*, 113(2):239–281.

Cortés, P. (2013). The Feminization of International Migration and Its Effects on the Children Left Behind: Evidence from the Philippines. *mimeo*.

Cox Edwards, A. and Ureta, M. (2003). International Migration, Remittances, and Schooling: Evidence from El Salvador. *Journal of Development Economics*, 72(2):429–461.

Davidson, R. and MacKinnon, J. G. (2004). *Economic Theory and Methods*. Oxford University Press, New York, NY.

Docquier, F. and Rapoport, H. (2012). Globalization, Brain Drain, and Development. *Journal of Economic Literature*, 50(3):681–730.

Duflo, E. (2003). Grandmothers and Granddaughters: Old Age Pensions and Intrahousehold Allocation in South Africa. *The World Bank Economic Review*, 17(1):1–25.

Foerster, R. F. (1925). *The Racial Problems Involved in Immigration from Latin America and the West Indies to the United States*. U.S. Department of Labor, Washington, DC.

Hanson, G. H. and Woodruff, C. (2003). Emigration and Educational Attainment in Mexico. *mimeo*.

Kandel, W. and Kao, G. (2000). Shifting Orientations: How US Labor Migration Affects Children's Aspirations in Mexican Migrant Communities. *Social Science Quarterly*, 81(1):16–32.

Kandel, W. and Kao, G. (2001). The Impact of Temporary Labor Migration on Mexican Children's Educational Aspirations and Performance. *International Migration Review*, 35(4):1205–1231.

Massey, D. S. and Zenteno, R. (2000). A Validation of the Ethnosurvey: The Case of Mexico-US Migration. *International Migration Review*, 34(3):766–793.

Mcbride, G. M. (1923). *The Land Systems of Mexico*. Condé Nast Press, Greenwich, CO.

McKenzie, D. and Rapoport, H. (2007). Network Effects and the Dynamics of Migration and Inequality: Theory and Evidence from Mexico. *Journal of Development Economics*, 84(1):1–24.

McKenzie, D. and Rapoport, H. (2011). Can Migration Reduce Educational Attainment? Evidence from Mexico. *Journal of Population Economics*, 24(4):1311–1358.

McKenzie, D., Stillman, S., and Gibson, J. (2010). How Important is Selection? Experimental VS. Non-Experimental Measures of the Income Gains from Migration. *Journal of the European Economic Association*, 8(4):913–945.

Miranda, A. (2011). Migrant Networks, Migrant Selection, and High School Graduation in Mexico. In Polachek, S. W. and Tatsiramos, K., editors, *Research in Labor Economics, Vol. 33*, chapter 8, pages 263–306. Emerald Group Publishing Limited.

Mishra, P. (2007). Emigration and Wages in Source Countries: Evidence from Mexico. *Journal of Development Economics*, 82(1):180–199.

Mountford, A. (1997). Can a Brain Drain be Good for Growth in the Source Economy? *Journal of Development Economics*, 53(2):287–303.

Palafox, J. C., Prawda, J., and Velez, E. (1994). Primary School Quality in Mexico. *Comparative Education Review*, 38(2):167–180.

Santibañez, L., Vernez, G., and Razquin, P. (2005). Education in Mexico: Challenges and Opportunities. Technical report, RAND Corporation.

Schoellman, T. (2012). Education Quality and Development Accounting. *The Review of Economic Studies*, 79(1):388–417.

Solon, G., Haider, S. J., and Wooldridge, J. (2013). What Are We Weighting For? *NBER Working Paper*, 18859.

Stock, J. H. and Yogo, M. (2002). Testing for Weak Instruments in Linear IV Regression. *NBER Technical Working Paper*, 284.

Yang, D. (2008). International Migration, Remittances and Household Investment: Evidence from Philippine Migrants' Exchange Rate Shocks. *The Economic Journal*, 118(April):591–630.

Table 1: How Different Channels Work

	Remittance	Separation	Brain Drain	Allocation
General effect	Positive	Negative	Negative	Positive
During migration	Positive	Negative	Negative?	Positive
More income/education	Negative	Positive	Positive	Negative
Older children	Negative?	Positive?	Negative	Negative?
Girls	Positive	Positive	Positive	Positive

Figure 1: States Surveyed in the Sample (in Grey)

Table 2: Popular Destinations by Community

Destination	No. of Communities Associated
Austin-San Marcos, TX	1
Charlotte-Gastonia-Rockhill, NC-SC	2
Chicago, IL	11
Dallas, TX	3
Denver, CO	3
Houston, TX	1
Las Vegas, NV-AZ	1
Los Angeles-Long Beach, CA	17
Louisville, KY-IN	1
Minneapolis-St. Paul, MN-WI	2
New York, NY	3
Oakland, CA	1
Orange County (*sic*), CA	1
Philadelphia, PA-NJ	2
Phoenix-Mesa, AZ	1
Portland-Vancouver, OR-WA	2
Reading, PA	1
San Diego, CA	1
San Francisco, CA	1
San Jose, CA	4
Stockton-Lodi, CA	1
Tulsa, OK	1
Total	61

Figure 2: States with Communities Preferring Chicago (top) and Los Angeles (down)

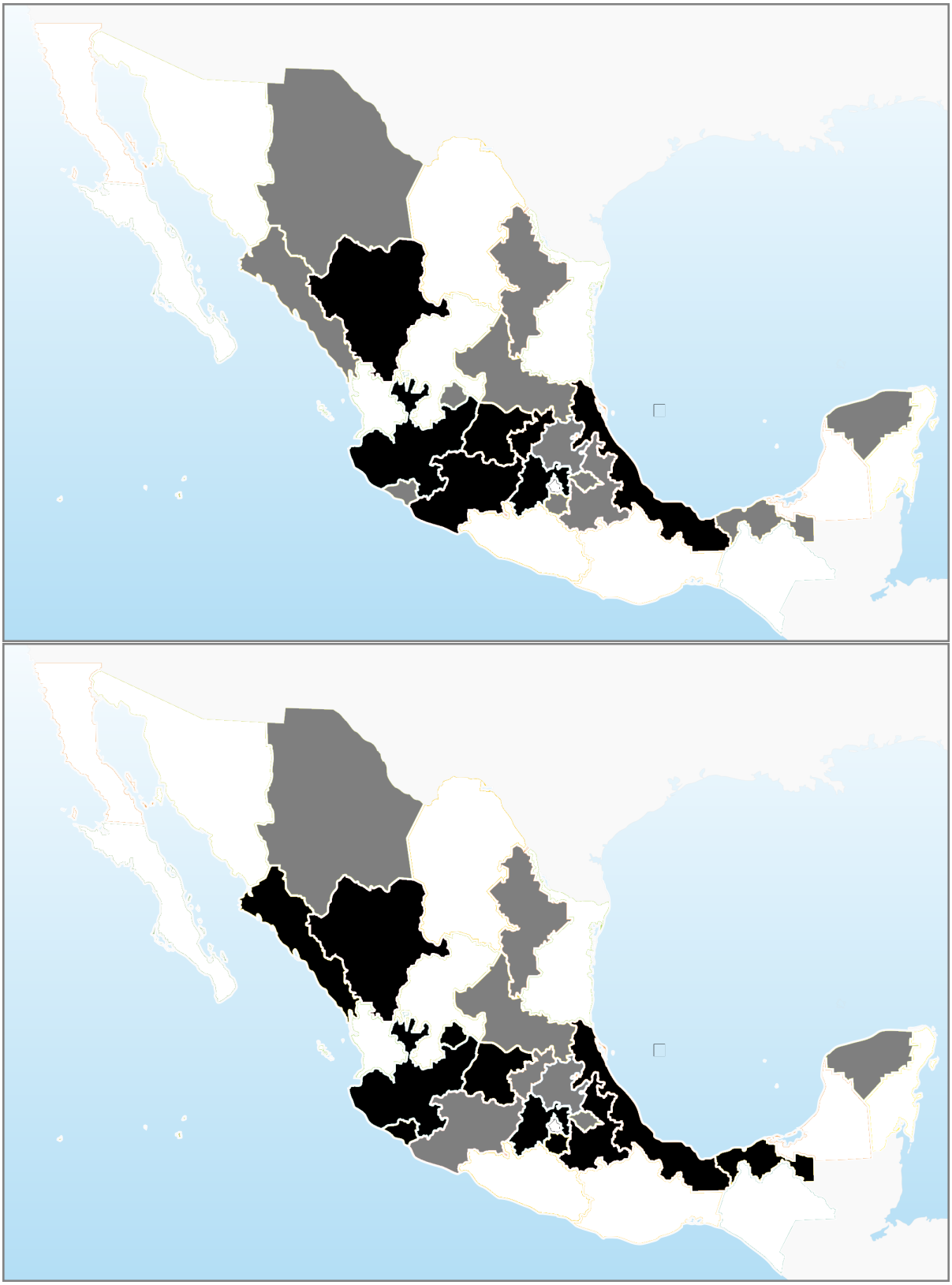

Table 3: Descriptive Statistics for Rural Children 11-19 Years old

	Full Sample	w/ Migrant Father	w/o Migrant Father	Difference
Father's education	6.42	5.61	6.84	-1.23
	(4.33)	(3.63)	(4.60)	
Mother's education	6.17	5.83	6.35	-0.52
	(3.81)	(3.45)	(3.98)	
Child's age	15.08	14.93	15.16	-0.23
	(2.57)	(2.59)	(2.56)	
Child's education	7.75	7.52	7.86	-0.34
	(2.71)	(2.68)	(2.72)	
Number of children	3.71	3.86	3.63	0.23
in the household	(1.85)	(1.98)	(1.78)	
HH income	28271	29052	27932	1120
(1997 Peso)	(43027)	(61580)	(31788)	
Child is female	50.1%	51.3%	49.5%	
Obs.	7064	2420	4644	
% in sample	100%	34.3%	65.7%	

Figure 3: Histogram of Years of Education, by Father's Migrant Status

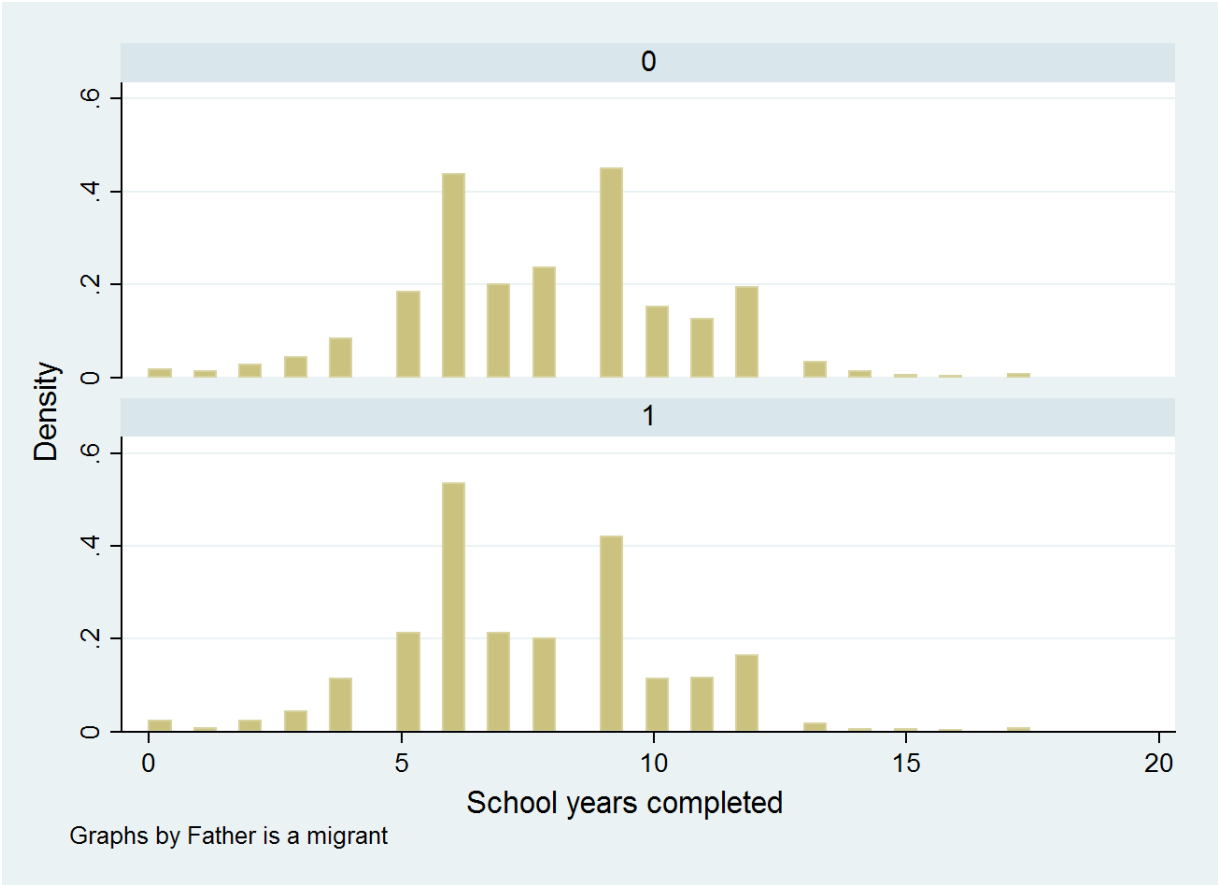

Table 4: First-stage Results

Dependent variable	Father has been a migrant	
Unemployment rate	-0.0244**	-0.0285***
at destination	(0.00955)	(0.00879)
Migration population	0.0000755**	0.0000743**
in 1925	(0.0000348)	(0.0000357)
Age of child	-0.0185	-0.0339
	(0.0307)	(0.0278)
Age of child squared	0.000180	0.000714
	(0.00105)	(0.000956)
Child is female	0.0121	0.00982
	(0.00993)	(0.00909)
Father's education	-0.0153***	-0.0151***
	(0.00338)	(0.00276)
Mother's education	0.00470	0.00456
	(0.00450)	(0.00356)
No. of children	0.0155*	0.00897
in household	(0.00823)	(0.00653)
Household income	3.06e-07	
	(2.34e-07)	
No. of secondary schools	0.0500	0.0337
in *Municipio* per 1000 resident	(0.0976)	(0.0950)
Birth order	-0.0254**	-0.0217**
	(0.0116)	(0.00983)
Home ownership rate	-0.0140	-0.0129
in 1910	(0.0128)	(0.0115)
Obs.	4381	7064
F-statistic	8.51	10.04
Prob. > F	0.0006	0.0002
R-squared	0.0644	0.0559

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 5: Effect of Migration Status on Years of Education

	OLS 1	IV 1	OLS 2	IV 2
Father has been	0.0152	-1.44**	0.0257	-1.34**
a migrant	(0.112)	(0.700)	(0.0780)	(0.655)
Age of child	2.17***	2.14***	2.17***	2.13***
	(0.154)	(0.165)	(0.124)	(0.127)
Age of child squared	-0.0520***	-0.0516***	-0.0521***	-0.0516***
	(0.00559)	(0.00590)	(0.00455)	(0.00452)
Child is female	0.226***	0.272***	0.254***	0.275***
	(0.0536)	(0.0506)	(0.0479)	(0.0481)
Father's education	0.108***	0.0847***	0.114***	0.0916***
	(0.0123)	(0.0190)	(0.0107)	(0.0156)
Mother's education	0.118***	0.119***	0.115***	0.121***
	(0.0112)	(0.0113)	(0.0104)	(0.0110)
No. of children	-0.114***	-0.0791**	-0.0976***	-0.0802***
in household	(0.0350)	(0.0362)	(0.0280)	(0.0273)
No. of secondary schools	0.0587	0.147	0.0793	0.133
in *Municipio* per 1000 resident	(0.205)	(0.223)	(0.251)	(0.274)
Birth order	0.0168	-0.0449	0.0205	-0.0115
	(0.0455)	(0.0495)	(0.0427)	(0.0477)
Household income	-8.69e-07	-2.67e-07		
	(5.43e-07)	(6.58e-07)		
Home ownership rate	0.0317	0.00417	0.0587	0.0516
in 1910	(0.0391)	(0.0396)	(0.0378)	(0.0359)
Obs.	4381	4381	7064	7064
R-squared	0.4420	0.3800	0.4321	0.3754

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 6: Effect of Migration Status on Years of Education: Age-Gender Groups

	Female 11-15	Female 16-19	Male 11-15	Male 16-19
Father has been	-0.583	-2.24*	-0.941*	-1.90**
a migrant	(0.709)	(1.23)	(0.558)	(0.999)
Age of child	2.23***	3.47	1.99***	-1.67
	(0.493)	(2.49)	(0.521)	(2.17)
Age of child squared	-0.0572***	-0.0925	-0.0478**	0.0536
	(0.0193)	(0.0719)	(0.0202)	(0.0624)
Father's education	0.0345*	0.120***	0.0437***	0.160***
	(0.0199)	(0.0312)	(0.0168)	(0.0252)
Mother's education	0.0820***	0.190***	0.0609***	0.161***
	(0.0134)	(0.0256)	(0.0130)	(0.0246)
No. of children	-0.0160	-0.137***	-0.0254	-0.130**
in household	(0.0289)	(0.0389)	(0.0377)	(0.0532)
No. of secondary schools	0.162	0.169	0.123	0.155
in *Municipio* per 1000 residents	(0.253)	(0.411)	(0.263)	(0.436)
Birth order	-0.0647	-0.266*	-0.131***	-0.234*
	(0.0584)	(0.149)	(0.0440)	(0.138)
Home ownership rate	0.132***	0.0563	0.0914**	-0.0605
in 1910	(0.0426)	(0.0549)	(0.0413)	(0.0575)
Obs.	1907	1634	1925	1598
R-squared	0.3541	0.1043	0.3115	0.1514

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 7: Probit Results

	Probit 1	IV-Probit 1	Probit 2	IV-Probit 2
Father has been	0.0089	1.17***	0.0202	0.976***
a migrant	(0.0794)	(0.423)	(0.0559)	(0.345)
Average marginal effects	0.2%	26.6%	0.4%	22.1%
Age of child	-0.0156	0.00655	-0.0146	0.0167
	(0.179)	(0.164)	(0.128)	(0.122)
Age of child squared	0.0105*	0.00875	0.0105	0.00873**
	(0.00577)	(0.00574)	(0.00410)	(0.00419)
Child is female	-0.184***	-0.176***	-0.162***	-0.159***
	(0.0488)	(0.0472)	(0.0411)	(0.0388)
Father's education	-0.0872***	-0.0513**	-0.0922***	-0.0647***
	(0.0120)	(0.0243)	(0.00827)	(0.0165)
Mother's education	-0.0803***	-0.0719***	-0.0844***	-0.0797***
	(0.0103)	(0.0134)	(0.00902)	(0.00974)
No. of children	0.0577***	0.0269	0.0556***	0.0391**
in household	(0.0162)	(0.0214)	(0.0145)	(0.0161)
No. of secondary schools	0.0442	-0.0212	0.0107	-0.0239
in *Municipio* per 1000 resident	(0.139)	(0.145)	(0.130)	(0.134)
Birth order	0.0872**	0.104***	0.0790**	0.0905**
	(0.0406)	(0.0378)	(0.0397)	(0.0378)
Household income	-2.77e-06	-3.36e-06*		
	(1.95e-06)	(1.95e-06)		
Home ownership rate	-0.00942	-0.0141	-0.0152	-0.0167
in 1910	(0.0328)	(0.0331)	(0.0258)	(0.0246)
Obs.	4381	4381	7064	7064

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 8: Effect of Migration Status on Years of Education Completed: Interaction

	Father's Education	Mother's Education	Household Income
Father has been a migrant	-4.44***	-3.49***	-1.83***
	(1.21)	(0.990)	(0.609)
Migrant × Column variable	0.586***	0.449**	0.0000106
	(0.194)	(0.183)	(8.53e-06)
Column variable	-0.0318	-0.0119	-6.97e-06
	(0.0411)	(0.0525)	(5.15e-06)
Obs.	4381	4381	4381
R-squared	0.3060	0.3624	0.3695

Regressions use same set of controls as specification IV1 in Table 5.

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 9: Effect of Migration Status on Years of Education Completed: by Parents' Education

	Father's Education$\leq$ 6	Father's Education$>$ 6	Mother's Education$\leq$ 6	Mother's Education$>$ 6
Father has been a migrant	-1.51**	0.248	-1.39**	0.792
	(0.649)	(0.889)	(0.653)	(1.40)
Obs.	2800	1581	2966	1415
R-squared	0.2884	0.6503	0.3103	0.6369

Regressions use same set of controls as specification IV1 in Table 5.

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 10: Effect of Migration Status on Years of Education Completed: Interaction, by Children's Gender

	Father's Education		Mother's Education	
	Boys	Girls	Boys	Girls
Father has been a migrant	-5.39***	-4.00***	-3.00***	-5.07***
	(1.76)	(1.18)	(1.15)	(1.22)
Migrant × Column variable	0.683**	0.492***	0.276*	0.782***
	(0.269)	(0.187)	(0.164)	(0.273)
Column variable	-0.00942	-0.0527	0.00600	-0.0707
	(0.0524)	(0.0440)	(0.0507)	(0.0832)
Obs.	2224	2157	2224	2157
R-squared	0.2212	0.3564	0.3457	0.2783

Regressions use same set of controls as specification IV1 in Table 5.

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level

Table 11: Effect of Migration Status on Years of Education Completed: Timing

	All migrants	Child was born	Child was 6	Child was 11
Father last left for migration after...	-1.39**	-2.67**	-3.20**	-4.50**
	(0.680)	(1.32)	(1.55)	(2.13)
Obs.	4381	4381	4381	4381
R-squared	0.3875	0.2850	0.2638	0.2414
% in migrant children	100%	67.45%	49.85%	28.83%

Regressions use same set of controls as specification IV1 in Table 5.

*: significant at 10% level

**: significant at 5% level

***: significant at 1% level