The Intergenerational Effects of Paternal Migration on Schooling and Work: What Can We Learn from Children's Time Allocations?*

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December 3, 2010

Abstract

This paper explores the short-run effects of a father's U.S. migration on his children's schooling and work outcomes in Mexico. To get around the endogeneity of paternal migration, I use individual fixed effects and instrumental variables estimation (FEIV) where the instrumental variables are based on U.S. city-level employment statistics in two industries popular with Mexican immigrants. Overall, the estimates suggest that in the short-run, children reduce study hours and increase work hours in response to a father's U.S. migration. Decomposing the sample into sex- and age-specific groups suggests that this is mainly driven by the effects of paternal migration on 12-15 year-old boys. These results are consistent with a story in which the immediate aftermath of a father's migration is one of financial hardship that is borne in part by relatively young children.

JEL: O15; J12; J13; J22: J24; F22

Keywords: migration; education; child labor; time allocation; father absence; left behind

*For their helpful comments at various stages of this work, I would like to thank Doug Bernheim, Luigi Pistaferri, Aprajit Mahajan, John Pencavel, Terra McKinnish, Alfredo Cuecuecha, Fernando Lozano, Gordon Dahl, Benjamin Hansen, Prakash Kannan, Kevin Mumford, Brian Cadena, participants of the public, labor and development groups at Stanford University, two anonymous referees, and Co-editor Duncan Thomas. David McKenzie and Chris Woodruff were instrumental in obtaining and advising me on cleaning the main data set. Comments from participants at the AEA meetings, Pacific Conference for Development Economics, Northeast Universities Development Consortium, and BREAD summer school in development economics were also helpful. This research was supported by the Leonard W. Ely and Shirley R. Ely Graduate Student Fund through a grant to the Stanford Institute for Economic Policy Research. All errors are mine alone.

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1 Introduction

Until recently, research on migration from Mexico to the U.S. was mostly focused on outcomes for the migrants themselves or the communities receiving them (Borjas, 1987, 1994; Munshi, 2003). However, with mounting evidence suggesting that migration often involves the temporary separation of the migrant from his family in Mexico (Reyes, 1997), recent attention has turned to the consequences of migration for the children of migrants left behind. Does parental migration lead to better or worse outcomes for these children who will one day enter the Mexican and maybe even U.S. labor markets? This paper adds to that literature by examining the immediate, short-run impact of parental migration, asking how a father's U.S. migration affects the intensive and extensive margins of children's participation in school and work in Mexico. An investigation of the short-term impact is instructive as it paints a portrait of the experience of families left behind at the time of migration, when families may be supporting the migrant as opposed to the other way around. In addition, the short-term impact on variables capturing children's interest in school can turn out to have important long-term consequences, such as when a child drops out and finds it difficult to return.

The empirical estimation is complicated by the fact that migration is in all likelihood correlated with the same factors that determine children's schooling, either because parent and child share some important traits or because they are exposed to the same economic shocks. Some researchers have relied on variation in historical state migration rates for identification, as in Hanson and Woodruff (2003) who find a positive effect of migration on the schooling of younger children and McKenzie and Rapoport (2006) who find evidence of a negative effect of migration on schooling for older children. Cuecuecha (2009) attempts to distinguish the effects of international migration from those of remittances, but uses current migration and remittance rates in sending communities as instrumental variables, which arguably capture contemporaneous peer effects and thus fail the exclusion restriction. Historical migration rates, while certainly better than contemporaneous, may also be correlated with current levels of community development in Mexico and thus could affect children's outcomes directly.

Other studies use economic conditions at the destination to instrument for migration. Amuedo-Dorantes, et al. (2008) estimate the impact of remittance receipt on school attendance in Haiti by using earnings and employment data from the U.S. and the Dominican Republic to predict remittance receipt. Their results suggest that while remittances increase the likelihood of school attendance, there is also a mitigating effect of household disruption for children in migrant households. Yang (2008) uses variation in exchange rate appreciation based on migrants' destinations to show that remittances result in an increase in child schooling. Most closely related to the current paper, Amuedo-Dorantes and Pozo (2010) rely on unemployment and wages in U.S. destination states to identify the effects of the level and volatility of remittances on expenditure patterns in Mexico. In related work, McKenzie and Rapoport (2007) explore the possibility of using aggregated unemployment rates in the U.S. state to which migrants were most likely to travel in an attempt to identify the effects of migration prevalence on inequality in Mexico. Unfortunately, they run into a problem of potentially weak instruments with this strategy, and thus focus attention on results using historical migration rates as instruments instead.

The identification strategy used in this paper follows in the same spirit as these latter papers, but also takes advantage of panel data to address unobserved heterogeneity at the individual level that may lead to a non-causal correlation between parental migration and children's outcomes. First, I use individual child-level fixed effects (FE) to address the possibility that parents and children are shaped by common genetics and experience that may affect both the probability of paternal migration and child outcomes like schooling and work. Second, I use instrumental variables (IV) characterizing employment conditions in specific industries in the U.S. city which the potential migrant would most likely select as a destination. I argue that these variables do not directly affect the child's outcomes at home in Mexico and demonstrate that they help to predict U.S. migration for Mexican fathers.

Besides the focus on the short-term impact of paternal migration, another major contribution of this paper is to use time use data to examine the effects of migration on the intensive margin of schooling investment, that is, the number of hours per week which a child devotes to studying. While most studies have focused on schooling outcomes, I also add to the literature by examining the effect of paternal migration on hours of work. Since the panel data set used here covers only about a year, the research question can be thought of as addressing the short-run effects of paternal migration on children's schooling and work outcomes, as opposed to studies which focus on educational attainment, an inherently longer-term consequence of migration. I focus on paternal U.S. migration because Mexican fathers are much more likely to migrate than Mexican mothers and paternal domestic migration has not been found to significantly affect child outcomes (Antman, 2010b).

Overall, I find that the FEIV results are broadly suggestive of children reducing study hours in response to a father's U.S. migration and provide some evidence of an increase in work hours outside the home. The relatively large magnitudes of the effects are consistent with a significant decrease in school participation and increase in work participation outside the home, which I also document as a binary outcome. Decomposing the sample into sex- and age-specific groups shows that these results are largely driven by the responses of 12-15 year-old boys.

The paper proceeds as follows. Section 2 discusses the possible channels through which paternal migration could affect children's outcomes. Section 3 reviews the empirical strategy used to surmount problems of endogeneity and discusses possible threats to the identification strategy. Section 4 reviews the data and summary statistics, including the distributions of the time use variables. Section 5 presents the estimation results from the FEIV regression. Section 6 performs robustness checks to address concerns about identification and attrition. Section 7 concludes with a discussion of possible interpretations of the results.

2 Background

There are several channels through which a father's migration abroad might affect the schooling and work decisions of his children living at home. Conventional wisdom tends to focus on the possibility that a migrant father may send home remittances that are higher than the wages he could have earned at home, thus relaxing the household resource constraint and enabling children to focus on schooling and reduce work hours. While several studies find evidence supporting the remittances hypothesis (Cox-Edwards and Ureta, 2003; Alcaraz et al. 2010; Yang, 2008), it is well-acknowledged that migration carries non-pecuniary effects that may not be similarly positive. Most notably, these effects include paternal absence from the home and family disruption which has been found to have negative consequences for children in the developed world (Ginther and Pollak, 2004; Grogger and Ronan, 1995; Sandefur and Wells, 1997). While Mexican households differ in their reliance on extended family for support, even if the presence of other adults is a common occurrence in migrant households (Nobles, 2006), children may still suffer from the absence of their father in particular. Nevertheless, paternal absence is but one effect included in the overall impact of paternal migration and cannot be separately identified in the current study.

Another important consideration is the elapsed time at which the impact of migration is measured. If the father is not immediately successful in finding U.S. employment or if there is a period of time which he must devote to costly travel and job search, in the short-run his family may have to take one or more of their children out of school and into the workforce to compensate for the loss of the father's domestic wages. Put simply, if migrants are unable to send remittances in the first year after migrating or if the family has to send money to support the migrant abroad, there should be no positive effect of remittances seen in the short time horizon examined in this paper.

In this way, this paper's focus on the short-term impact of migration may be consistent with Stark's (1991) model in which migration is a contractual agreement where the family at home insures the father for taking on the risks associated with migrating in the short-run. In the long-run, the migrant repays the family by insuring them against the risks of undertaking some new investment, whether it be a new agricultural technology, business, or even the continued education of children. While the findings in this paper may be consistent with the short-run implications of that model, due to the short time horizon of the outcomes observed here, this study naturally has limited insight into the long-run effects of migration. It could be the case that the signs and magnitudes of the impact of migration on children's outcomes are significantly different over a longer time horizon, even a few more years, when migrants may be more fully capable of sending remittances. Nonetheless, given the possibility that short-term outcomes like dropping out of school may have longer term consequences, an examination of the impact of migration in the short-run is useful.

In addition, a father's migration may also alter the household bargaining equilibrium, shifting authority over household consumption and investment decisions to the mother who may be more likely to invest more resources in her children's schooling. This effect may also have a gendered component that results in increased expenditures on girls relative to boys (Antman, 2010c) and an improvement in the schooling of girls over boys as seen in Antman (2010b). It may also be the case that a father's migration affects children's expectations of the return to an additional year of schooling in Mexico. Just as some studies have found the return to foreign education in the U.S. to be relatively low (Bratsberg and Ragan, 2002; Gonzalez, 2003; Friedberg, 2000), it may be that a father's migration experience teaches his children that Mexican education is not well-rewarded in the U.S.[1] This is similar to the argument made in the brain gain/brain drain literature wherein opportunities to migrate affect educational investments at home. Consistent with this hypothesis, deBrauw and Giles (2006) find a negative relationship between internal migration opportunities and high school enrollment in Chinese rural villages. While Boucher, et al. (2005) find that international migration from rural Mexico to the U.S. does not significantly affect schooling investments of non-migrants, the overall short-run impact of paternal migration on child schooling remains theoretically uncertain and an open empirical question.

[1] Kandel and Kao (2000) offer suggestive evidence that children of migrants have lower educational goals than children without the same level of migration exposure.

3 Empirical Strategy

Since the primary goal is to estimate the effect of the father's current migration on his child's schooling, the simplest econometric framework might begin by estimating the following equation:

$$S_{i,t} = \beta MigrantDadUS_{i,t} + \gamma\prime X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where the dependent variable, $S_{i,t}$, denotes schooling of the child in Mexico, a variable that could equal (1) how many hours per week the child spends studying, including hours spent in school or (2) a dummy variable indicating whether he studies at all, a proxy for school enrollment. I also assess the impact of paternal migration on child work outcomes by using (3) weekly hours of work outside the home, and (4) a binary indicator for whether the child reports any work hours outside the home (work participation) as dependent variables. The vector of covariates $X_{i,t}$, includes education, education squared, and a set of dummies to account for the year of observation.[2]

The effect of interest is captured by the coefficient on the $MigrantDadUS_{i,t}$ variable which is an indicator equal to one if the father is currently in the U.S. and zero otherwise. Effectively, this means that the reference group in the analysis includes children whose fathers are present as well as children whose fathers are not present, such as the case of children whose parents have separated as well as children whose fathers have migrated domestically.

[2] Other potentially relevant covariates such as mother's education, for example, will be fixed over time and are thus unnecessary in the fixed effect model used in this paper. While it is tempting to include additional household composition variables that might change over time, such as the number of adults present, these variables may be endogenous to the migration decision as well, and thus I omit them from the analysis.

While internal migration is highly prevalent in Mexico (Nobles, 2006) and it would be instructive to include domestic migration in the analysis here, additional instruments that would identify such an effect are not available. However, under an alternative identification strategy, Antman (2010b) considers the causal effects of domestic versus international migration on educational attainment and finds no significant impact of domestic migration, suggesting that we do no fundamental damage by including them in the base group. This may be due to the fact that domestic migrants are not as fully absent from their homes as international migrants or do not earn significantly more than they would in their home communities.

As discussed above, one concern with estimating equation (1) is that OLS estimation methods will yield biased estimates of β since the $MigrantDadUS_{i,t}$ variable is endogenous. One source of endogeneity is the relationship forged by genetics and experience that results in a correlation between unobserved components that influence the educational choices of the child and the migration choices of his father. The panel nature of the data allows a simple solution to correct for this type of endogeneity: individual fixed effects. Thus, the regression model can be expressed as:

$$S_{i,t} = \beta MigrantDadUS_{i,t} + \gamma\prime X_{i,t} + \eta_i + \nu_{i,t}, \tag{2}$$

where η_i captures observed and unobserved heterogeneity at the individual child level. Nevertheless, there could still be some source of endogeneity that varies over time, such as the case where, because of a shock to household income, the father is compelled to migrate and the child is forced to change his schooling choices. To deal with this problem, I propose a set of instrumental variables that will only influence the child's outcomes through their effect on the father's migration status. The proposed instrument set is based on labor market conditions in the U.S. city where the father was most likely to migrate in the month prior to the month when the survey was taken.[3] Since they describe economic conditions in the recent past in the destination country, they can be taken to affect the father's decision to migrate without influencing the child in the home country directly. A complete description of the construction of these instrumental variables is provided in the data section below.

The main empirical strategy then amounts to estimation of equation (2) above by instrumental variables, where migration status today is estimated via the following first-stage regression:

$$MigrantDadUS_{i,t} = \pi\prime Z_{it} + \theta\prime X_{i,t} + u_i + \varepsilon_{i,t}, \tag{3}$$

where Z_{it} is a vector of instrumental variables excluded from equation (2). The set of variables Z_{it} are comprised of the employment levels in two migrant-popular industries in the U.S. city to which the father was likely to migrate. I estimate the results for all children ages 12-18 as well as separately by sex and age groupings. Since the FEIV approach involves using repeated observations of children from the same family in different time periods, I cluster the standard errors at the level of the household to allow for arbitrary correlation

[3]As mentioned above, U.S. economic indicators have been used as instrumental variables to predict migration in other studies (McKenzie and Rapoport, 2007; Amuedo-Dorantes, et al., 2008; Amuedo-Dorantes and Pozo, 2010). Bauer, Epstein, and Gang (2002) also use migration destination data from the MMP to distinguish between herd and network effects driving the phenomenon of immigrant clustering in the United States.

within families and across time.[4]

The main threat to this identification strategy lies in the exclusion restriction necessary for instrumental variables estimation. First, it is possible that U.S. economic conditions affect child outcomes directly, perhaps because the U.S. and Mexican business cycles move together, and Mexican economic conditions will certainly affect the child's schooling and work outcomes. To address this concern, in the robustness section, I include the Mexican unemployment rate in the regression as well. This variable is available at the monthly level in the city in which the child resides, so I match it by the month in which the survey was taken. The unemployment data are constructed by Mexico's statistical agency, INEGI, based on the same Mexican labor force survey which I use in this paper, so there should be no concern about the quality of the match.[5]

Another, less plausible, threat to identification is the possibility that children are currently deciding whether to migrate to the U.S. themselves and may thus be affected directly by U.S. economic conditions. If this is the case, it is surely more pertinent for older children, who are far more likely to be considering migration independently than their younger peers. Focusing on the results for younger children, 12-15 years-old, mitigates this concern.

[4] Dahl and Lochner (2005) use an FEIV strategy and argue that clustering should be at the level of individuals, but in a later version of that paper (Dahl and Lochner, 2008) they take a more conservative approach and instead cluster at the level of the family.

[5] Available at http://dgcnesyp.inegi.org.mx/.

4 Data

The data I use to examine the intergenerational consequences of migration on child schooling and work outcomes come from Mexico's *Encuesta Nacional de Empleo Urbano* (ENEU), the national urban labor force survey collected by Mexico's national statistical agency, INEGI, for the years 1990-2001.[6] The ENEU is a short panel data set at the household level which asks detailed labor and education questions of households for each of five quarters. Questions are asked of all household members 12 years of age and older and information is collected on hours spent studying, doing household chores (domestic work), and working outside the home.

A key benefit of this data set is the fact that interviewers keep track of who leaves the household in every period and the location where the absent person is currently located. In the case of migration, however, in general one can only identify whether the person migrated to the U.S. and not the specific location within the U.S. It is also not possible to know how long the person has been away from the home if his departure is not observed during the sample period. Another drawback of the data is that since the focus of the survey is the physical residence, entire households moving away from their homes are not followed. One of the main advantages, however, is that as a panel data set, it allows examination of the immediate consequences of migration for those households where the father is observed to be present in one period and absent in another. Since it is primarily an urban data set, it also permits an exploration of the effects of migration on urban households who are often ignored in many migration studies that focus on rural areas.

[6] Only the first two quarters of 2001 are available for analysis here.

The main outcome variables of interest are the reported weekly hours spent studying and weekly hours engaged in work outside the home.[7] The variable describing hours spent studying is peculiar in that it includes the number of hours spent in school and one cannot distinguish between hours spent in the classroom and hours spent preparing for class. One possibility is that knowledge flows from international migration make children more efficient at studying, implying that a decrease in study hours is not necessarily a negative outcome. Due to this limitation in the data, however, it is not possible to detect whether this is the case. Unfortunately, there is also no question regarding whether the child is enrolled in school, so the best indicator for whether the child attends school is whether he spends any hours studying. Levison, et al. (2000, 2008) provide good overviews of the ENEU data set, particularly the time-use variables for adolescents.

To match these child observations in Mexico to the U.S. city employment data that will operate as instrumental variables, I use data from the Mexican Migration Project (MMP107).[8] The MMP is a collaboration between Princeton University and the University of Guadalajara covering the years 1982-83 and 1987-2004. It is a publicly available data set containing information on the migration patterns and general characteristics of households in Mexico. It also has detailed accounts of the life-long labor and migration histories of the household head and his or her spouse. Massey and Zenteno (2000) provide an overview of the MMP data and present evidence that it reflects a reasonably accurate profile of Mexican migrants to the United States.

[7] Readers interested in the results for domestic work hours (household chores) can refer to Table A2 of the appendix.

[8] Available at http://mmp.opr.princeton.edu/.

To construct my instrumental variables, I limit the study to communities that are sampled in both the ENEU and the MMP. This consists of 13 metropolitan areas throughout Mexico.[9] I then use the MMP107 to identify the U.S. city to which the migrants from the Mexican areas were most likely to say they last migrated. Given the historic concentration of migrants in some regions of the U.S., there are understandably few destinations. Table 1 shows the distribution of observations over the cities in Mexico and their matches to cities in the U.S. Almost 80% of the sample are from Mexican cities where Los Angeles was the predominant destination on the last migration trip in the MMP, followed by Chicago, El Paso, and San Diego. Since the MMP is often regarded as primarily a rural data set, one concern might be that matching between an urban and rural data set, even though they are geographically close, is not appropriate. The fact that there are so few U.S. cities regarded as potential destinations, however, alleviates concerns regarding the validity of the match between the ENEU and the MMP.[10] The ability of the instruments to predict migration, as shown in the first-stage regression results below, also attest to the relatively strong link between the Mexican and U.S. data sources.

Once I have identified the U.S. city to which potential migrant fathers are most likely to move, I link the child observations with employment data from the Bureau of Labor

[9] These cities are Puebla, Leon, San Luis Potosi, Chihuahua, Guadalajara, Ciudad Juarez, Tijuana, Durango, Acapulco, Morelia, Oaxaca, Zacatecas, and Irapuato.

[10] Due to the limited number of migrant destinations, one concern might be that the instrumental variables provide insufficient variation, despite the fact that they do also vary over time. Interested readers can consult Figure A1 of the appendix for graphs displaying the extent of variation in the instrumental variables. Table A1 in the appendix goes through robustness checks testing the strength of the instrumental variables under alternative clustering scenarios.

Statistics on two of the top three industries which attract Mexican immigrants (Grieco and Ray, 2004): (1) the construction sector and (2) the accommodation and food sector.[11] City-wide data on employment in these sectors are available from 1990 to 2001.[12] It is expected that these variables will act to stimulate migration, i.e. when employment in these sectors is high indicating a boom in those industries important to migrants, potential migrants will be more likely to make the trip. Since the current study focuses on schooling outcomes, I exclude the summer months of June, July, and August, effectively excluding one quarter from the panel. In light of the fixed effects analysis, I also limit the sample to children who are observed at least twice during the panel, so the remaining group of children will have been observed between two and four times. Due to attrition, this results in a drop of approximately 11 percent of the usable sample.

One concern is that this approach will leave us with a non-representative sample if attritors and non-attritors are significantly different, particularly in a study where households with migration experience may be more likely to move and thus fall out of the survey (Thomas, et al. 2001, 2010). To address this issue, Section 6 considers the likely impact of attrition on the estimates presented below. After matching the data sets together, the resulting sample consists of children of household heads ages 12-18 living in Mexican cities sampled by the ENEU that are also sampled in the MMP spanning the years 1990-2001.

[11] For El Paso, the definition of the these sectors is slightly different from the rest of the cities. Construction includes the natural resource sector and the accomodation and food sector is entirely leisure. Nevertheless, since the IVs vary at the city-time level and individuals are assigned the same U.S. city throughout the analysis, we can expect this difference in definition not to matter for the estimation with individual FEs.

[12] Available at http://www.bls.gov/data/home.htm.

4.1 Summary Statistics

Table 2 shows descriptive statistics of the sample of 22,642 child-period observations (7,391 children) in this study. The average household includes about 6.5 members, mother and father's educational attainment are about 6 and 6.75 years, respectively, and father's age is about 46 years. Fifty-two percent of the sample is male with an average age of 15 years and average years of education around 7.5. While in principle Mexican schooling may be compulsory through grade 9, in practice, many children drop out well in advance of that. Sixty-two percent of the sample used here participates in school, as measured by the indicator for whether they report studying at all. About 75 percent of 12-15 year-olds report positive study hours compared with only 45 percent of those over age 15, suggesting that the main focus for the study hours variable may be on the younger group of children. At the same time, about one quarter of the full sample is employed outside the home (reporting positive work hours) and about two-thirds of the sample performs some domestic work. Average weekly study hours, including time spent in school, are about 21 hours (with a median of 30 hours) while child work inside and outside the home amount to about 10 hours each.

The average time use statistics capture both the intensive and extensive margins, so it is also useful to examine the distributions of the time use variables explicitly. Since this paper relies on individual fixed effects for identification, an important sample to consider here is those children who experienced a change in father's migration status over the course of the panel survey. Figures 1a and 1b show the cumulative distribution functions for hours of study, and hours of work by father's migration status for the 364 children (1131 child-period observations) who experienced such a change. Figure 1a shows that the distribution for children whose fathers are U.S. migrants lies entirely to the left of the distribution for children whose fathers are not in the U.S. This provides suggestive support for the proposition that paternal migration discourages children's focus on schooling, although Figure 1b is more ambiguous as to an implication for child work hours.

While these distributions tell us something about the observed differences between child outcomes when fathers were in the U.S. and when they were not, these differences may arise for reasons other than having a migrant parent in the U.S. For instance, a family may have suffered a household-level shock that made it more likely for the father to migrate and for the child to study fewer hours. The addition of the instrumental variables analysis proposed above will help us determine the extent to which the differences seen here are due to the experience of paternal migration.

5 Results

5.1 First Stage

A thorough analysis using instrumental variables begins with a demonstration of the strength of the instrumental variables proposed. Table 3 shows the results from the first-stage regression from equation (3) where the dependent variable is an indicator for whether the father is currently in the U.S. and the excluded instruments are the employment levels in the construction and accommodation and food industries in the U.S. city to which the father was most likely to migrate given his home community in Mexico. These results should be interpreted within the framework of the linear probability model.

Both construction employment and accommodation and food employment levels are lagged one month behind the month of the survey. The point estimates indicate that an increase in lagged construction employment by 100,000 would correspond to an increase in the probability of paternal migration by 4.3 percentage points and an increase in lagged accommodation and food employment by 100,000 would increase the probability of paternal migration by 10.3 percentage points.[13] Although the former estimate is only statistically significant at the 20 percent level, the latter is significant at the 5 percent level. In addition, the F statistic on the excluded instruments is 11.94, indicating the relative strength of the instrumental variables used here (Staiger and Stock, 1997; Stock and Yogo, 2002; Murray, 2006).[14]

5.2 FEIV Results for All Children

Table 4 shows the results of the IV analysis of equation (2) with individual fixed effects (FEIV).[15] Unfortunately, the use of individual fixed effects effectively prohibits the use of limited dependent variable maximum likelihood methods, so the linear probability model

[13] Since the average employment levels in the construction and accomodation and food industries are around 158,000 and 315,000, respectively, this would constitute a large increase in employment.

[14] Another option would be to cluster at the individual level, as in the FEIV strategy used by Dahl and Lochner (2005). This raises the first stage F statistic to 21.9, and the construction and accommodations point estimates are statistically significant at the 10 and 1 percent levels, respectively. While the first stage F statistic is generally sensitive to the level of clustering of the standard errors, it remains close to 10 even when clustering at the level of the Mexican metropolitan area and the errors are bootstrapped to take into account the small numbers of clusters (Bertrand, et al. 2004; Cameron, et al. 2008). The first stage results from these and other alternative clustering scenarios can be found in Table A1 of the appendix.

[15] This is implemented in STATA using the xtivreg2 command (Schaffer, 2007).

is employed here for the participation outcomes. Similarly, a linear FEIV model is used instead of a censored regression model, which some might favor. Column (1) shows the results for the main outcome variable of interest, hours spent studying per week. In terms of the response to paternal migration, we see that having a father in the U.S. reduces study hours by approximately 35.6 hours per week. While this magnitude may seem large, it is again important to note that this value includes the number of hours spent in school, and is close to the median of the distribution for those children who report positive study hours. Although some may contend that a drop in study hours is not necessarily bad if studying has become more efficient, the large magnitude of these results indicate that this is not likely to be the case, and instead point to the likelihood that this represents a significant drop in time spent in school.

Column (2) investigates whether this is indeed a school participation decision, and finds a decrease in the probability of participating in school with the migration of a father, but the point estimate of -0.46 is not statistically significant. Columns (3) and (4) show a corresponding increase in work participation. Column (3) shows an increase of about 61 hours worked per week, a magnitude close to the 95th percentile of the distribution for children reporting positive work hours. The large magnitude of this result points to a significant increase in hours of work outside the home, consistent with a shift to full-time work and thus the observed increase in work participation.[16]

Since there are two instrumental variables used in the analysis, an overidentification test is also possible, although it can be argued that if both instrumental variables are measuring

[16] The value of the coefficient estimate is actually above one, a result that can sometimes be found when using the linear probability model.

the same economic forces, it provides limited information (Murray, 2006). Nevertheless, in all of the preceding regressions, we can fail to reject the null hypothesis of valid instruments. Thus, the overall effects of paternal migration appear to decrease a child's focus on schooling and increase his focus on work outside the home.

5.3 FEIV Results by Sex-Age Group

Table 4 also decomposes the sample into four sex-age groups and runs the same FEIV regression. As is often the case, however, the instruments are much weaker by subgroup, and the F statistic on the excluded instruments is only above 10 for the youngest group of boys, 12-15. The remaining results should thus be interpreted with caution. Nevertheless, the table documents a similar response to paternal migration for younger boys and girls (around –52 study hours for both), but a statistically significant drop in school participation only for younger boys. There is also a statistically significant increase in work hours for younger boys around 32 hours per week, as well as an increase in work participation.

As for older children, 16-18 years-old, Table 4 does not document any statistically significant changes in their behavior in response to paternal migration. This makes sense since it is the younger children that are around the age at which a person would complete the average educational attainment seen in this sample (7.5 years). It is thus the younger group of children who we should expect to be most affected by parental migration, and in fact it appears that 12-15 year-old boys are the main group to be hurt by it.

A natural follow-up question to consider is whether there are comparable results for domestic work hours (household chores) that might show girls taking on additional responsibility at home just as boys are working more elsewhere. These results are provided in Table A2 of the appendix. Overall, I find that there are no statistically significant effects on domestic work hours or participation for boys or girls. Nevertheless, the point estimates are generally negative for boys and positive for girls, with the magnitude of the response for younger girls appearing to be larger than that of younger boys. While these effects are imprecisely estimated and cannot be clearly interpreted, they allude to the possibility that girls may in fact be substituting domestic work for study hours in the same way that boys are shifting their focus from schooling toward work outside the home.

6 Robustness

6.1 Exclusion Restriction

As mentioned above, one concern with the FEIV strategy used here is that U.S. employment statistics are affecting children's schooling and work decisions directly. For instance, some might be concerned that children are currently considering migrating themselves, thus implying an exclusion restriction violation. However, the fact that the results shown above are mainly driven by the younger group of children who are less likely to migrate mitigates this concern. Another possible threat to the exclusion restriction is the possibility that U.S. labor market conditions affect the migration propensity of other members of the community which in turn affects the level of development in the community and the schooling and work habits of peers. While this channel may have spillover effects on the children in this study, these types of effects are likely to be second-order, and could be argued to bias results against finding the effects seen here.

A more plausible case for an exclusion restriction violation is the possibility that since the Mexican and U.S. business cycles tend to move together, the U.S. economic data may in fact be capturing economic changes in Mexico and thus affecting children directly. To address this concern, I include the unemployment rate in the Mexican city in which the child resides directly in the regression model. The results from the FEIV regressions on the full sample with this additional control can be found in Table 5.

The Mexican unemployment rate is statistically significant in both the study hours and participation as well as the work hours and participation regressions and operates as expected, raising the number of study hours and dropping the number of work hours when unemployment is high. At the same time, the F statistic on the excluded instruments from the first stage regression remains around 12, indicating that the strength of the instruments has not been compromised as a consequence of the added control variable. Most importantly, compared with the results from Table 4, where no such control was included, the signs and magnitudes of the effect of paternal migration on children's outcomes are all very similar, suggesting that these results are robust to these concerns over the exclusion restriction.

6.2 Attrition

Another concern raised above is that since the FEIV strategy requires children to be observed at least twice, the results may be compromised if children who attrit from the survey are significantly different from those in the usable sample. This is of particular concern in a migration study since attrition is likely to be correlated with the same observable and unobservable factors that determine geographic mobility (Thomas, et al. 2001, 2010). Table 6, Panel A shows that "attritors," defined as those children with only one usable observation, do in fact display significant differences from those children observed at least twice. They are more likely to have a migrant father in the U.S., are slightly older and slightly more educated. They are also less likely to report positive study hours, report lower study hours on average and are more likely to be employed with more work hours on average. Thus, it seems reasonable to consider the possibility that the results may be different for the sample of non-attritors and those of attritors.

While I cannot run the FEIV analysis on the sample of children observed only once, I can gauge the extent to which this is likely to be a problem by considering the results for the sample of children that never attrit, that is, those who are observed for the full four quarters possible, and compare them with children who attrit at some point but appear in the survey at least twice. Table 6, Panel B presents the differences among these two groups of people, distinguished by the number of periods in which they are observed in the sample. Here, "non-attritors" are defined as those children observed in all four periods possible, while "attritors" are defined as those who are only in the survey for two or three periods. As in the previous comparison, Panel B shows that attritors are more likely to have a migrant father in the U.S., are less likely to study and more likely to work outside the home, and display additional observable differences when compared with the "non-attritor" group.

To investigate whether the results are significantly different for the "attritor" and "non-attritor" samples defined above, Table 7 presents the FEIV regression results separately for each group. Panel A shows a statistically significant increase in work hours and work participation associated with the migration of a father to the U.S. for the "non-attritor" sample. Although the magnitudes of the point estimates fall slightly, similar results are seen in Panel B for the work outcomes for the sample of "attritors." In addition, the sample of "attritors" shows a statistically significant decrease in study hours and study participation. As is often the case, the first stage F statistics are smaller once the sample is split, and consequently, the results should be interpreted with caution. Nonetheless, this analysis provides additional support for the notion that the overall drop in child study hours and rise in child work hours observed above is not an artifact of the identification strategy.

7 Conclusion

This paper set out to identify the short-run effects of a father's current migration to the U.S. on his children's study habits and participation in school while also examining the impact on children's work hours and employment outside the home. The contributions of this study, by focusing on time-use data, exploiting a panel data set, and using instrumental variables based on the U.S. destination city, point to a negative short-term effect in the period immediately following paternal migration. Overall, the FEIV results are suggestive of children decreasing their study hours and participation in school in response to a father's U.S. migration, especially for younger children. At the same time, there is evidence that boys, ages 12-15, are also increasing their work hours and work participation outside the home when their fathers migrate.

The finding that younger boys respond to paternal migration by decreasing their focus on school and increasing their attention on work outside the home is consistent with a story in which the period immediately following a father's migration is marked by financial hardship for families in Mexico who may be financing the father's trip and also waiting for him to find gainful employment in the U.S. It may be that boys, more so than girls, are called upon to take more financial responsibility for the household during this period and thus shift their focus from schooling toward work outside the home. This interpretation would fit well with the short-run implications of Stark's (1991) model of migration as a contractual agreement where the family insures the migrant against risk in the short-run and the migrant returns the favor in the long-run. Nonetheless, as I am unable to decompose the overall change into components due to a delay in remittances, father absence, and learning about lower returns to Mexican education abroad, it may be that one of the latter two effects is instead driving the results.

While these findings appear to stand in contrast with the view that international migration has a net positive effect on family members left behind, I am also unable to rule out the possibility that in the long-run children are better off as a result of their father's migration. Using a different identification strategy and data set, Antman(2010b) finds that a Mexican father's international migration leads to an increase in ultimate educational attainment for his daughters. The finding that sons are not similarly advantaged in the long-run would be consistent with the results seen here if the short-run effects of migration on boys are in the end found difficult to reverse.

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Table 1: Match between Mexican Labor Force Survey (ENEU) and Mexican Migration Project (MMP)

Mexican City	U.S. City	Observations
Acapulco	Los Angeles	1637
Chihuahua	Los Angeles	768
Ciudad Juarez, Chihuahua	El Paso	1518
Durango	Los Angeles	3859
Guadalajara	Los Angeles	3767
Irapuato, Guanajuato	Los Angeles	1138
Leon	Los Angeles	888
Morelia	Los Angeles	1557
Oaxaca	Los Angeles	1545
Puebla	Los Angeles	1163
San Luis Potosi	Chicago	1972
Tijuana	San Diego	1140
Zacatecas	Los Angeles	1690
	Total	22642

Source: ENEU, 1990-2001, and MMP107.
U.S. city identified as most likely response to question of destination on last U.S. migration from MMP107.
Number of observations from ENEU, 1990-2001.

Table 2: Descriptive Statistics for Children, 12-18 years-old

	Median	Mean	Std. Dev.
Household Size	6	6.43	2.38
Mother's Education	6	5.98	4.15
Father's Education	6	6.74	4.90
Father's Age	45	46.25	8.43
Child is Male	1	0.52	0.50
Child's Age	15	15.04	1.95
Child's Years of Education	7	7.52	2.39
Child Studies	1	0.62	0.48
Child is Employed	0	0.24	0.43
Child Does Domestic Work	1	0.66	0.47
Child's Hours of Study	30	20.84	17.35
Child's Hours of Work Outside Home	0	9.38	18.20
Child's Hours of Domestic Work	7	9.85	10.63
Number of Children		7391	
Number of Child-Period Observations		22642	

Table 3: Father's US Migration, First Stage Regression

	(1) Father in US
US City Construction Employment, monthly lag	0.043
	[0.034]
US City Accommodation & Food Employment, monthly lag	0.103
	[0.041]**
Observations	22642
Number of FEs	7391
Number of clusters (households)	4331
F stat on excluded instruments	11.94

Other controls: education level and its squared value, year dummies
Robust standard errors clustered at household level in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Children's Time Use and Paternal Migration
IV Regression with Individual Fixed Effects

	(1)	(2)	(3)	(4)
	Study		Work	
	Hours	Participates	Hours	Participates
Full Sample				
Father in US Coeff.	-35.576	-0.459	60.668	1.598
Standard Error	[17.164]**	[0.430]	[19.962]***	[0.509]***
Observations	22642	22642	22642	22642
Number of FEs	7391	7391	7391	7391
Overidentification test p value	0.617	0.65	0.538	0.838
First Stage F Stat on Excluded IVs	11.94	11.94	11.94	11.94
Boys, 12-15				
Father in US Coeff.	-52.373	-1.131	31.686	1.058
Standard Error	[22.621]**	[0.578]*	[18.338]*	[0.522]**
Observations	6492	6492	6492	6492
Number of FEs	2150	2150	2150	2150
Overidentification test p value	0.06	0.173	0.316	0.686
First Stage F Stat on Excluded IVs	10.18	10.18	10.18	10.18
Girls, 12-15				
Father in US Coeff.	-52.78	-0.832	25.518	0.605
Standard Error	[26.639]**	[0.638]	[18.689]	[0.515]
Observations	6015	6015	6015	6015
Number of FEs	1978	1978	1978	1978
Overidentification test p value	0.9	0.685	0.981	0.51
First Stage F Stat on Excluded IVs	5.95	5.95	5.95	5.95
Boys, 16-18				
Father in US Coeff.	14.12	1.031	230.341	3.681
Standard Error	[57.220]	[1.690]	[167.117]	[2.898]
Observations	4944	4944	4944	4944
Number of FEs	1735	1735	1735	1735
Overidentification test p value	0.791	0.469	0.687	0.409
First Stage F Stat on Excluded IVs	1.31	1.31	1.31	1.31
Girls, 16-18				
Father in US Coeff.	-6.854	0.52	15.298	1.684
Standard Error	[32.510]	[0.867]	[36.358]	[1.042]
Observations	4497	4497	4497	4497
Number of FEs	1560	1560	1560	1560
Overidentification test p value	0.056	0.054	0.828	0.531
First Stage F Stat on Excluded IVs	5.25	5.25	5.25	5.25

Other controls: education level and its squared value, year dummies
Robust standard errors clustered at household level in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Robustness to Mexican Economic Conditions

IV Regression with Individual Fixed Effects, Controlling for Economic Conditions in the Mexican City

	(1)	(2)	(3)	(4)
	Study		Work	
	Hours	Participates	Hours	Participates
Full Sample				
Father in US	-34.651	-0.444	59.665	1.58
	[16.998]**	[0.427]	[19.766]***	[0.504]***
Mexican City Unemployment Rate	0.66	0.014	-0.693	-0.014
	[0.195]***	[0.005]***	[0.213]***	[0.005]**
Observations	22642	22642	22642	22642
Number of FEs	7391	7391	7391	7391
Overidentification p value	0.556	0.699	0.484	0.79
First Stage F Stat on Excluded IVs	12.02	12.02	12.02	12.02

Other controls: education level and its squared value, year dummies

Robust standard errors clustered at household level in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Descriptive Statistics at Baseline Survey by Measures of Attrition

Panel A: "Non-Attritors" (observed more than once) versus "Attritors" (observed once)

	(1) Non-Attritors		(2) Attritors		(3) Diff. (1-2)
	Mean	Std. Dev.	Mean	Std. Dev.	
Father in U.S.	0.011	0.103	0.049	0.216	-0.038 ***
Household Size	6.462	2.355	6.238	2.350	0.223 ***
Mother's Education	5.952	4.124	5.964	4.195	-0.012
Father's Education	6.713	4.861	6.632	4.831	0.082
Father's Age	45.859	8.485	45.713	9.127	0.146
Child is Male	0.525	0.499	0.524	0.500	0.001
Child's Age	14.781	1.994	15.418	2.265	-0.637 ***
Child's Years of Education	7.327	2.392	7.491	2.541	-0.164 ***
Child Studies	0.648	0.478	0.529	0.499	0.120 ***
Child is Employed	0.230	0.421	0.284	0.451	-0.054 ***
Child Does Domestic Work	0.658	0.475	0.647	0.478	0.010
Child's Hours of Study	21.647	17.107	17.513	17.569	4.133 ***
Child's Hours of Work Outside Home	8.745	17.675	11.532	19.848	-2.788 ***
Child's Hours of Domestic Work	9.802	10.639	10.045	11.298	-0.243
Number of Children	7391		2669		

Panel B: "Non-Attritors" (observed 4 times) versus "Attritors" (observed 2 or 3 times)

	(1) Non-Attritors		(2) Attritors		(3) Diff.(1-2)
	Mean	Std. Dev.	Mean	Std. Dev.	
Father in U.S.	0.007	0.085	0.013	0.112	-0.006 **
Household Size	6.557	2.367	6.409	2.347	0.148 ***
Mother's Education	6.099	4.186	5.870	4.087	0.229 **
Father's Education	6.847	4.973	6.640	4.796	0.207 *
Father's Age	46.004	8.216	45.779	8.629	0.225
Child is Male	0.510	0.500	0.533	0.499	-0.023 *
Child's Age	14.441	1.714	14.968	2.109	-0.527 ***
Child's Years of Education	7.200	2.197	7.397	2.490	-0.197 ***
Child Studies	0.691	0.462	0.625	0.484	0.067 ***
Child is Employed	0.188	0.391	0.253	0.435	-0.065 ***
Child Does Domestic Work	0.682	0.466	0.644	0.479	0.038 ***
Child's Hours of Study	23.235	16.695	20.772	17.269	2.463 ***
Child's Hours of Work Outside Home	6.713	15.715	9.864	18.573	-3.151 ***
Child's Hours of Domestic Work	10.019	10.261	9.683	10.841	0.335
Number of Children	2625		4766		

Table 7: Children's Time Use and Paternal Migration for "Non-Attritors" & "Attritors"
IV Regression with Individual Fixed Effects

Panel A: "Non-Attritors" (Observed in all 4 periods possible)

	(1)	(2)	(3)	(4)
	Study		Work	
	Hours	Participates	Hours	Participates
Father in US Coeff.	-2.842	0.656	57.033	1.718
Standard Error	[19.060]	[0.544]	[22.970]**	[0.631]***
Observations	10500	10500	10500	10500
Number of individual FEs	2625	2625	2625	2625
Overidentification p value	0.345	0.883	0.858	0.87
First stage F Stat on excluded instruments	8.44	8.44	8.44	8.44

Panel B: "Attritors" (Observed in 2 or 3 periods)

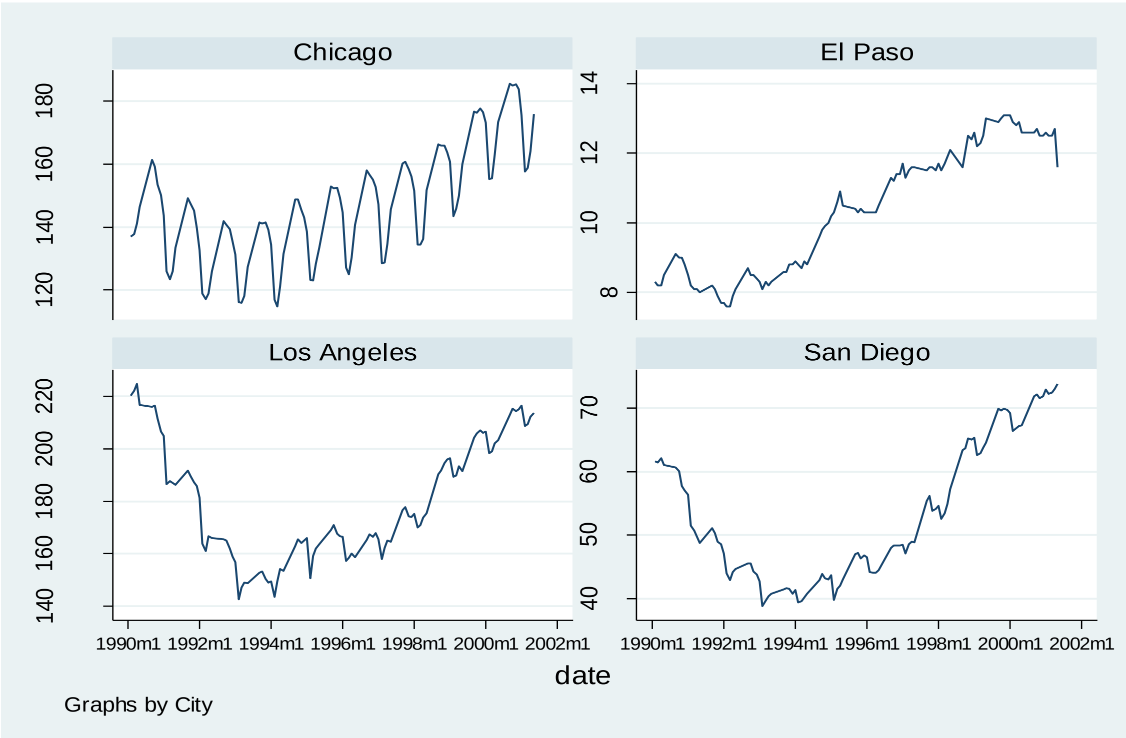
	(1)	(2)	(3)	(4)
	Study		Work	
	Hours	Participates	Hours	Participates
Father in US Coeff.	-75.742	-1.91	45.191	0.994
Standard Error	[29.576]**	[0.766]**	[24.816]*	[0.576]*
Observations	12142	12142	12142	12142
Number of individual FEs	4766	4766	4766	4766
Overidentification p value	0.924	0.769	0.377	0.58
First stage F Stat on excluded instruments	6.13	6.13	6.13	6.13

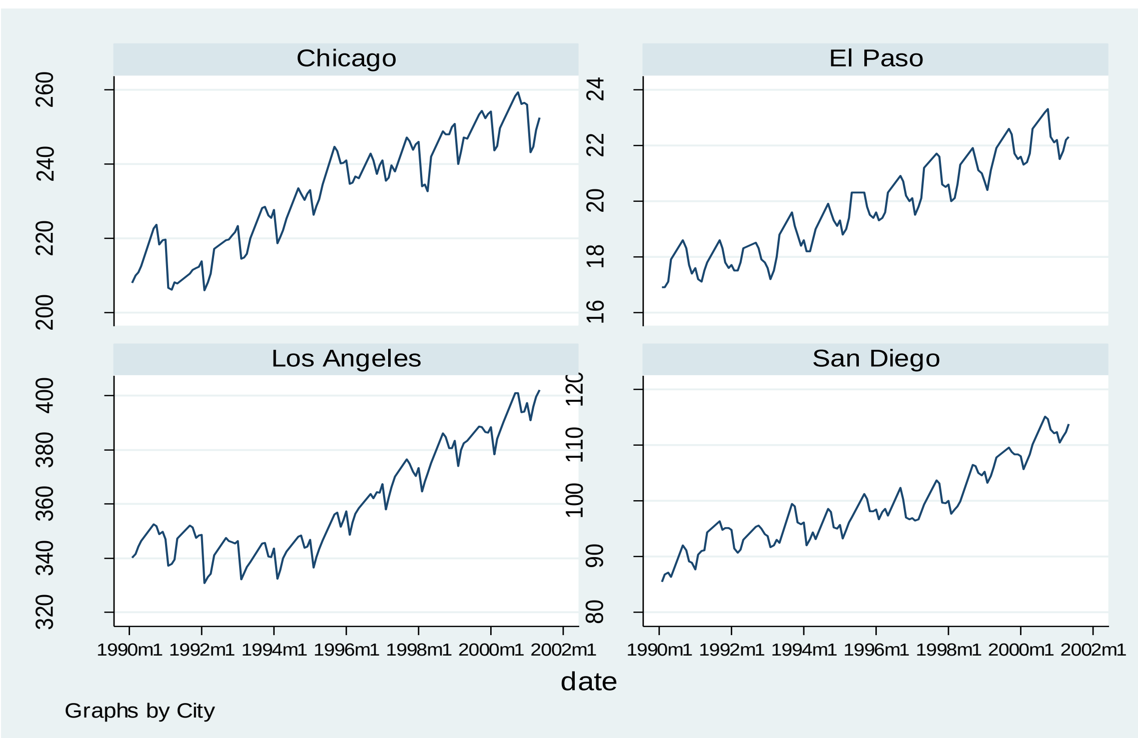
Other controls: education level and its squared value, year dummies

Robust standard errors clustered at household level in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Figure A1: Variation in Instruments





Appendix Table A1: First stage results under alternative clustering of standard errors

	(1)	(2)	(3)	(4)
	Individual child clusters	Household level clusters	US Destination City*First month to enter survey	Metro area in MX (bootstrapped with 500 replications)
	Father in US	Father in US	Father in US	Father in US
US City Construction Employment, monthly lag	0.043	0.043	0.043	0.043
	[0.023]*	[0.034]	[0.039]	[0.024]*
US City Accommodation & Food Employment, monthly lag	0.103	0.103	0.103	0.103
	[0.029]***	[0.041]**	[0.054]*	[0.056]*
Observations	22642	22642	22642	22642
Number of FEs	7391	7391	7391	7391
Number of clusters	7391	4331	357	13
F stat on excluded instruments	21.9	11.94	9.74	9.71

Other controls: education level and its squared value, year dummies

Robust standard errors clustered as indicated above

* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table A2: Paternal Migration and Children's Domestic Work

IV Regression with Individual Fixed Effects

	(1)	(2)
	Domestic Work	
	Hours	Participates
Full Sample		
Father in US Coeff.	3.177	-0.437
Standard Error	[10.649]	[0.533]
Observations	22642	22642
Number of FEs	7391	7391
Overidentification test p value	0.976	0.473
First Stage F Stat on Excluded IVs	11.94	11.94
Boys, 12-15		
Father in US Coeff.	2.053	-0.231
Standard Error	[10.577]	[0.700]
Observations	6492	6492
Number of FEs	2150	2150
Overidentification test p value	0.218	0.401
First Stage F Stat on Excluded IVs	10.18	10.18
Girls, 12-15		
Father in US Coeff.	19.028	0.447
Standard Error	[18.646]	[0.776]
Observations	6015	6015
Number of FEs	1978	1978
Overidentification test p value	0.113	0.747
First Stage F Stat on Excluded IVs	5.95	5.95
Boys, 16-18		
Father in US Coeff.	-25.013	-2.207
Standard Error	[36.826]	[2.722]
Observations	4944	4944
Number of FEs	1735	1735
Overidentification test p value	0.393	0.232
First Stage F Stat on Excluded IVs	1.31	1.31
Girls, 16-18		
Father in US Coeff.	14.53	0.17
Standard Error	[29.712]	[0.847]
Observations	4497	4497
Number of FEs	1560	1560
Overidentification test p value	0.744	0.315
First Stage F Stat on Excluded IVs	5.25	5.25

Other controls: education level and its squared value, year dummies

Robust standard errors clustered at household level in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%