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Abstract

This paper explores the short-run e¤ects 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 …xed e¤ects 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-speci…c groups suggests that this is mainly driven by the e¤ects 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 …nancial 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

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1 Introduction

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 for children in the developed world (Ginther and Pollak, 2004; Grogger and Ronan, 1995;

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.

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[1]

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:

$$S_{i;t} = \quad MigrantDadUS_{i;t} + {}'X_{i;t} + {}_{i;t}, \tag{1}$$

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 since the $MigrantDadUS$

within families and across time.[4]

The main threat to this identi…cation strategy lies in the exclusion restriction necessary for instrumental variables estimation. First, it is possible that U.S. economic conditions a¤ect child outcomes directly, perhaps because the U.S. and Mexican business cycles move together, and Mexican economic conditions will certainly a¤ect 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

4 Data

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

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 x

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

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 signi…cant at the 20 percent level, the latter is signi…cant 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 individ(i)Lt3r4h ihe9211(e)9(r)12(e) 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 e¢ cient, 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 signi…cant drop in time spent in school.

Column (2) investigates whether this is indeed a school participation decision, and …nds 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 signi…cant. 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 oft tdistribut5mldreile oft tdutu8 a 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 sibility 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 exunobservable 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 signi…cant decrease in study hours and study participation. As is often the case, the …rst stage F statistics are smaller once the sample is split, and consequently, the results should be interpreted with caution. Nonetheless, this analysis 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

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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)

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)
	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

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

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

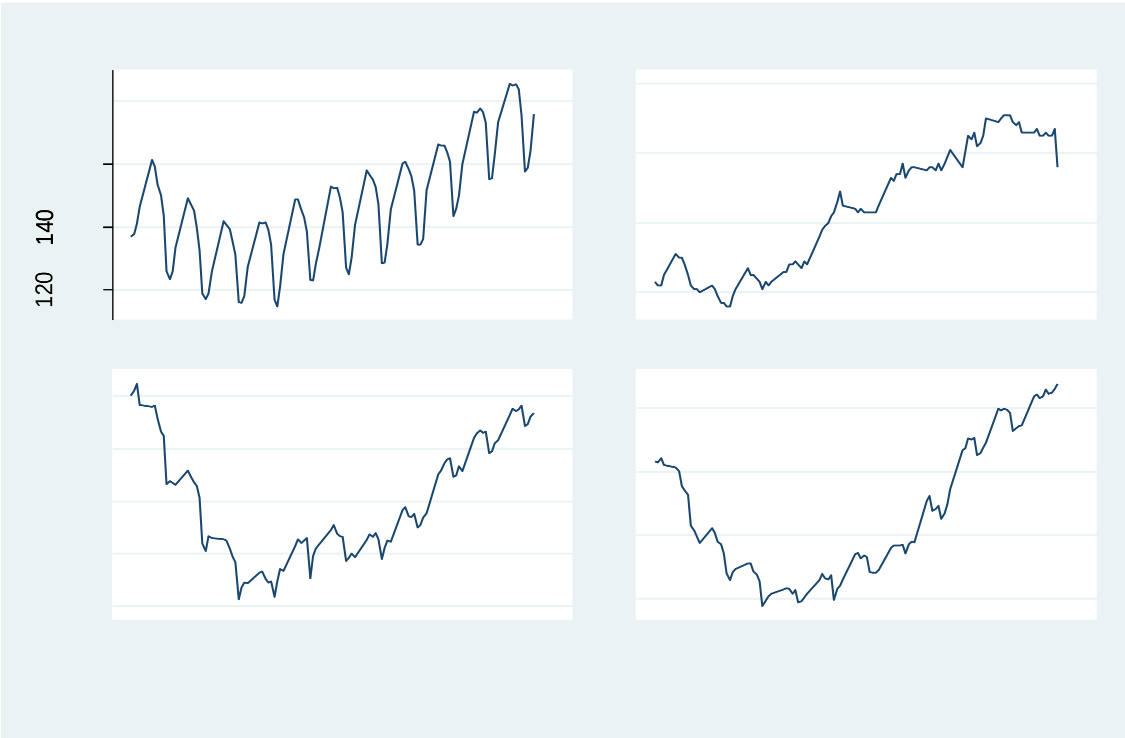
Panel B: "Attritors" (Observed in 2 or 3 periods)

	(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%



140
120

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
	0.043	0.043	0.043	0.043
	[0.023]*	[0.034]	[0.039]	[0.024]*
	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				