On the Determinants of Young Adult Outcomes: An Examination of Random Shocks to Children in Military Families

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We examine long-run outcomes for children of enlisted soldiers in the U.S. Army. We exploit conditional random variation in base assignments (residential location) and in the timing and frequency of moves. The disruptive effects of moving are large and increase as a child progresses through school; moving during high school lowers college enrollment by 2.5 percentage points and earnings at age 30 by 3 percentage points. Assignments in which the whole family is sent overseas (e.g. bases in Germany, Italy, UK, and Japan) have small positive effects on college enrollment and raise wages by 4 percentage points. Ten years in a county with one standard deviation higher test scores or percent BAs raises college enrollment by 4.7 percentage points. Location effects are larger later in a student's career. We confirm Chetty and Hendren's (2015) estimates of the impact of U.S. counties on mobility; their measure accurately predicts impacts on a child's college enrollment with a coefficient that approaches 1.

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I. Introduction

Social scientists have long been interested in how changes in childhood environment translate into impacts on long-run outcomes. For example, there are rich literatures on the causal effects from the Moving to Opportunity experiment (Katz, Kling and Liebman, and Chetty Katz and Ludvig), from changes in schools (Abdulkadiroğlu, Angrist, Dynarski, Kane, and Pathak 2011), from school desegregation (Billings, Deming and Rockoff 2014), from shocks to income, from adoption into different families (Sacerdote 2007 and Bjorkland, Lindahl and Plug 2006) or from changes in residential location (Chetty, Hendren, Kline and Saez 2014).

We contribute to this literature by considering long-run outcomes for children in military families. These children are subject to a series of random shocks to location. Our outcomes are college enrollment, earnings at ages 25 and 30, marital status, and zip code level income for the child's residence at age 30. We have several key research questions. First, how large is the causal impact from moving (changing residential location) on these outcomes? Does the effect vary by child age (or family demographics)?

Second, we test Chetty and Hendren's (2015) effects of exposure to a given US county on young adult college-going and earnings. Chetty and Hendren (2015) use the universe of all movers in U.S. federal income tax returns. We have a set of movers for whom the timing and location of the move is plausibly exogenous and uncorrelated with family background, child age, parental Armed Forces Qualification Test (AFQT) score, etc.

Third, we ask whether the whole family being sent overseas is potentially a positive experience for the child's long run development and outcomes.

Our identification strategy relies on quasi-random assignment processes of the U.S. Army. The military assigns its personnel, especially junior enlisted personnel, based on organizational needs and not individual preferences. We provide both institutional details and statistical evidence to support our approach, which has been used previously by economists in a variety of settings where endogenous relocation is a concern.

We find that moving is quite disruptive for children's outcomes, even in Army families which move frequently, receive assistance with moves and often have a support network of other military families (and sometimes access to Department of Defense Education Agency Schools). The negative effects of moving increase monotonically from pre-school to high school. High school moves decrease college enrollment by 2.5 percentage points and decrease earnings at age 30 by 3 percent.

We test Chetty and Hendren's (2016) estimates of the effects of exposure to a given county. We find that their measure is predictive of child outcomes (using our quasi-random moves). In predicting effects of exposure to a county, the Chetty-Hendren measure performs as well or better than other descriptive statistics such as county level income, poverty rates, test scores, or percent of people with four or more years of college. In some cases we reject the null that the effect of a location is similar across child ages; effects tend to be larger for older students.

We hypothesized that children would benefit from being sent overseas to Europe or Japan. Our theory was that the Department of Defense Education Agency Schools would provide a great deal of value added. And that exposure to a different culture and language would provide long term payoffs. We find some positive effects from overseas assignments on college going particularly during high school. We find positive and statistically significant effects on earnings for students who are overseas during high school.

While the impact of moving and changes in neighborhood characteristics during childhood on young adult outcomes is an important and interesting question in its own right, it is also important for understanding numerous tax policies. For example, attending college often involves utilizing Federal benefits aimed at easing the burden of education-related expenses. In future versions of this paper, we will also investigate whether living in a higher-education county leads to families being more likely to use the American Opportunity Tax Credit or the Lifetime Learning Credit. We will also ask whether children who spend more of their formative years in higher-income counties are less likely to take up the Earned Income Tax Credit and more likely to generate capital gains income, interest and dividend income, and self-employment income. Our study also contributes to our understanding of intergenerational changes in income inequality.

II. Prior Literature

Our paper builds on several literatures in social science. First, it contributes to the literature on the impacts of children's geographic mobility on their long-term outcomes. Prevailing wisdom and much of the existing work suggests that moving has negative effects on children's test scores, long term educational outcomes and likelihood of dropping out of high school. See for examples Audette, Algozzine, and Warden (1993), Rumberger (2003), Adam and Chase-Landsdale (2002), Hoffman and Johnson (1998), Hagen et al (1996). Coleman (1988) in particular argues that moving harms students by disrupting their peer relationships and social capital. Wood et al (1993) study children in the National Health Interview Survey and find that children who move frequently are twice as likely to repeat a grade and to have behavioral problems.

At the same time, there is a smaller but growing literature which finds that most of the negative effects of moving are attributable to selection, i.e. the pre-existing academic performance and family demographics of students who move. Alexander, Entwistle and Dauber (1993) examine a large sample of elementary students who change schools within Baltimore. They find that controlling for baseline scores explains most or all of the negative effects from moving.

Hanushek, Kain, and Rivkin (2003) is among the most thorough studies on the subject and examines math scores for student movers in Texas. When not controlling for prior achievement, moves depress math scores by 0.17 standard deviations in the year of the move. However, controlling for prior test scores reduces this impact to 0.03 standard deviations, though the disruption costs are larger for low income and non-white students.

Our contribution is to consider impacts from moving when the timing and location of moves is plausibly exogenous. Importantly we focus on the long run costs of moving including impacts on college going and earnings. We find that disruptive effects on earnings and college going are significantly larger for older students and probably larger than earlier results on test scores might have implied. Our results are consistent with Chetty, Hendren and Katz (2016) who find that, relative to younger movers in Moving to Opportunity, older children who moved in the same experiment experience disruption costs which are not offset by enough years of exposure in their new, lower poverty location.

We also add to the literature on the effects of place on young adult outcomes. Analyses of the Gatreaux program (Rosenbaum 1995, Rosenbaum De Luca and Miller 1999) and of the Moving to Opportunity Experiment (Katz, Kling, and Liebman 2001; Ludwig, Duncan, and Hirshfield 2001) suggest that neighborhoods have significant beneficial impacts on long run outcomes including behavior in school and health. Oreopolous (2003) and Jacob (2003) study families who relocate from housing projects. Oreoupolous does not find evidence that shifts in neighborhood influence earnings at age 30.

Chetty, Hendren, Kline and Saez (2014) is already among the most influential papers on this topic. The authors find that some cities in the US (e.g., San Jose) offer far more intergenerational income mobility than others (e.g., Charlotte). Chetty and Hendren (2015) extend this work by examining how exposure to different counties generates different outcomes in children's college going and income. They employ several strategies which suggest that their estimates of county level impacts are causal and not driven by selection. We propose to advance this literature by examining a sample in which location is plausibly exogenous and we ask whether the "Chetty-Hendren" measures are useful predictors of outcomes for the movers in our sample.

We also consider whether overseas moves benefit the children in military families. Many overseas assignments are "accompanied" moves in which the family moves with the service member. These include bases in Germany, the UK, Italy and Japan. We ask whether assignment to such a base offers long term benefits for the children in the family. Possible mechanisms could include learnings about another culture, learning another language or changes in a child's peer group.

Finally, our work is related to the literature on parental absences. When Army personnel are assigned to bases in Korea, the Middle East, or combat areas in general, these are typically unaccompanied assignments in which the family remains stateside. Angrist and Johnson (2000) found that deployment of a male service member in Gulf War I impacted spousal labor supply but had no impact on the likelihood that children were diagnosed with a disability. Lyle (2006) found that children of deployed service personnel saw test score decreases of 0.10 standard deviations. Engle Gallagher and Lyle (2010) and Hiew (1992) also find negative academic consequences for children with parents who are absent for military deployments.

III. Institutional Details, Data Description, Sample Construction, and Research Design

A. *Overview of the Army's Assignment Process*

Our analysis relies on the plausibly exogenous variation in assigned locations for enlisted personnel in the U.S. Army. Each year, the Army Human Resources Command (HRC) must fill hundreds of thousands of jobs at bases around the world (e.g., an Infantryman in Alaska or an Attack Helicopter Repairer in Korea). For reference, we provide data on the most common Primary Military Occupation Specialties (PMOS) for our sample in Appendix Table 3. Almost 10 percent of our sample are Infantrymen (PMOS 11B) and 4 percent are Motor Transport Operators (PMOS 88M).[1]

To make these assignments, HRC follows Department of Defense policy (i.e., Department of Defense Directive 1315.07 "Military Personnel Assignments") and Army Regulations (i.e., AR 600-14 "Enlisted Assignments and Utilization Management"), which prioritize the "needs of the Army" over individual preferences. The Army defines these needs based on the specific tasks that soldiers in an occupation do at each level of the military hierarchy (e.g., an Infantryman in the rank of Private does different work than an Infantryman in the rank of Sergeant and also different work from an Attack Helicopter Repairer in the rank of Private). Thus from HRC's perspective, service members with the same job and military rank are interchangeable, and the assignment process treats them as such. For any given year of assignments, a service member's assignment location is effectively random, conditional on their job specialty and their rank.

Service members typically change their duty assignment locations every 3 years but some assignments can go as long as 5-6 years. A histogram of assignment lengths in days is shown in Figure 8. The policy of fairly frequent moves is intended to serve several purposes. Frequent mixing is intended to promote cohesiveness across the Army and ensure that techniques developed at one base are migrated to other bases around the world. Mixing prevents knowledge and attitude silos in which methods and procedures vary drastically between two locations.

Given this unique and quasi-random assignment process, economists have exploited military assignments to overcome concerns over endogeneity in relocation decisions. For example, Angrist

[1] For a complete list of Army PMOS, see: http://army.com/info/mos/.

and Johnson (2000) study the effects of military relocations on divorce and spousal employment; Lyle (2006) documents the effects of parental absences and relocations on children's short-term academic achievement; Lleras-Muney (2010) documents adverse health effects for military children based on increased exposure to ozone; Carrell and Zinman (2014) provide suggestive evidence of adverse military labor market outcomes for Air Force personnel from access to payday lending, while Carter and Skimmyhorn (forthcoming) find no adverse effects on financial or labor market outcomes for Army personnel. Murphy (2017) evaluates peer effects in service members' educational decisions.

While the institutional rules and previous literature provide a strong prior for the quasi-random nature of Army assignments, we complete a few additional steps. First, we reviewed publicly available HRC documents and online information detailing the assignment process.[2] Second, our own anecdotal experiences in discussing assignments with enlisted personnel support our assumptions; people assigned to Germany, for example, had not requested such an assignment nor did they have any ability to switch. Finally, and most importantly, we show empirically that there is little correlation between base characteristics and personnel (or family) characteristics at baseline once we condition on specialty, rank and year of assignment. In the spirit of Altonji, Elder and Taber (2005) we argue that this lack of correlation between our observed characteristics and treatment suggests that any unobserved characteristics are also unrelated to our treatment.

Longer serving service members may have some degree of control over their assignments. Officers and more experienced enlisted personnel (those with 10 or more years of service) submit preferences for base assignments. Experience and anecdotes suggest that more seasoned enlisted personnel may be requested by commanders who know them, or they may obtain specific assignments as part of the reenlistment process. HRC personnel and researchers who have studied the assignment process (e.g., Lyle 2006, Burnam et al 1992, Segal 1986) agree that junior enlisted personnel have little influence in the location of their assignment. We consider junior personnel to be those with ranks of E1 (Private) through E6 (Staff Sergeant). We explain in Section II.C how we account for the influence of job specialty and rank.

[2] Special thanks to Major Fran Murphy for leading this effort.

Figure 1 is a map of assignments in the US made during the period of our data (1990-2011). The circle areas are proportional to the number of enlisted personnel assigned to that location over the time period. Some of the largest Army bases are labelled (e.g. Forts Drum, Hood, Campbell etc.). The exact number of assignments at the largest bases within the U.S. are shown in Appendix Table 1

Figure 2 shows the worldwide map and provides locations for assignments within and Outside the Continental US. (In the text that follows, we use the Army abbreviation OCONUS to refer to these assignments.) Some OCONUS assignments including Korea and the Middle East are not accompanied by family members. We currently drop these from our sample.

B. Data Description and Sample Construction

We rely on Army personnel data and Department of Defense (DEERS) data for our sample.[3] These data include information on Army service members and their children from 1990-2011 and comprise nearly 741,000 service members and their 1.5 million children. For each service member, we observe the location, start date and end date of every assignment along with their rank and PMOS at the time of assignment. We also observe when each service member first joined the Army, when he separated from the Army, and the type of discharge (known as Characterization of Service) he received. We have demographic information on each service member including gender, detailed race codes, home state, birth date, marital status and number of dependents. In addition, we have scores (by subject) on the Armed Forced Qualification Test (AFQT) and educational attainment. For each child, we know her birth date, age, gender, and race.

For each child, we construct indicator variables, $MOVED_0, \ldots, MOVED_{17}$, that are set equal to one if she moves at a given age between 0 through 17. Because a service member may not be enlisted throughout the entirety of one's childhood, for each age, a, we create an indicator variable, $MISSING_a$, that denotes these missing observations; in these instances, we also set the variable $MOVED_a$ equal to zero. We also construct two age-specific indicator variables to denote location assignments outside of the U.S.: (1) the indicator variable *OCONUS* is set equal to one if the assignment is anywhere outside of the continental U.S. (i.e., foreign countries, Hawaii, and

[3] The data were provided by the Office of Economic and Manpower Analysis (OEMA) at the U.S. Military Academy.

Alaska); and (2) the indicator variable *OCONUS_accompanied* is set equal to one if the foreign location is one to which military families would typically relocate their families.

For each domestic U.S. assignment, we construct several measures of county (or zip code) characteristics that a child experiences at each age. From the American Community Survey (ACS), we utilize information on county level percent with a B.A., percent with a high school diploma, percent of families below 150 percent of the poverty line, percent non-white, and median income. We use the 2005 ACS for these measures. From Chetty and Hendren (2016), we use their causal estimates of the impact of one year of exposure in the county upon (A) a child's college enrollment probability and (B) log earnings. We refer to these measures as the "Chetty-Hendren college effect" and the "Chetty-Hendren income effect." These measures are constructed for two different points in the parental income distribution: we use estimates for families at the 25^{th} percentile of U.S. income, which aligns closely with the incomes of the military families in our sample.

Because senior personnel may have some control over their location assignments, we construct age-specific indicator variables, $SENIOR_a$, which equals one if a child's parent has been in service for at least 10 years or has a rank of at least E6 at age a. We construct interaction terms between each of our moving and neighborhood variables and a location assignment occurring when a parent is "senior." In our baseline specifications, we only use assignments during which the parent was not senior.

We match the military children in our sample to administrative, population-based U.S. federal tax records between 1999 through 2014. We use several information returns, forms that are submitted by third parties to the Internal Revenue Service (IRS), to construct our key outcome variables. Each child's college attendance is determined using the Form 1098-T, which colleges submit to the IRS to report qualified educational expenses in a given year. We construct an indicator variable for having a 1098-T in any year between ages 17 and 22, and an indicator variable for having at least four years with a 1098-T between ages 17 and 22. Wage and salary income comes from Form W-2 and non-employee compensation comes from Form 1099-MISC. For brevity, we will refer to W-2 income as "wage income." Non-employee compensation contains income for contract work or temporary jobs, where an individual is not considered an employee by the firm. For each individual, we sum over the forms received across multiple employers, if relevant. We use these to construct earnings at ages 25 and 30. In addition, we collect several items reported on a tax return (Form 1040), including total income, adjusted gross income, marital status, and the number of children claimed.

We limit the sample to enlisted servicemembers (i.e., we exclude warrant and commissioned officers) who have at least one child aged 0 and 17 during their military service. We also restrict our sample to children born before 1997. This cutoff is dictated by our desire to observe young adult outcomes for children in the sample: all military children in our sample will be at least 18 by December 2014, the last year of our tax data. These restrictions reduce the sample to 337,661 service members with 632,975 children. Nearly 46 percent of these service members have only one child, and the remainder have multiple children. The greatest number of children associated with a service member is thirteen.

Data on the sample means are shown in Table 1. These means are calculated at the level of the child, meaning that, for example, a parent with two children will be counted twice. We first focus on columns (1) through (3), which provide summary statistics for all children in our sample. Panel A presents summary statistics for the demographic information contained in the Army data. Within our sample, 92 percent of the service members are male, and 51 percent of their children are male. Thirty five percent of service members are black, 8 percent are Hispanic, and 50 percent are white. Seventeen percent of service personnel were ever married. The average AFQT score is 54, where the scale is 1 to 99. Approximately 57 percent of service members graduated from high school or have a GED, and another 36 percent has some college education or an associate's degree. An additional 6 percent has a bachelor's degree, and 1 percent has a graduate degree.

In Panel B, we provide summary statistics on the geographic mobility of the children in our sample. On average, children in our sample move 2.3 times. Fewer than 2.5 percent of children in the sample experience no moves, and the maximum number of moves experienced by a child is 10. Overall, there are a significant number of movers during each developmental "period" of childhood that we examine.[4] Approximately 57 percent are stationed overseas at least once during

[4] Forty six percent of children move at least once during their pre-school ages (0-4), 61 percent move during elementary school (ages 5-10), 39 percent move during middle school (ages 11-13), and 36 percent move during high school (ages 14-17).

the panel. The average length of stay in one given location is 2.8 years (1015 days). Children are not generally observed during their entire childhoods; on average, we observe them for 6.6 years.

Panel C of Table 1 shows sample means and standard deviations for our outcomes of interest. Forty-nine percent of the military children ever attend college, defined by the presence of a 1098-T in any year between ages 18 and 22. Among the 487,000 children who are at least 21 as of December 2014, only 18 percent have at least four years with 1098-T. On average, wage income is $17,000 and $23,000 at ages 25 and 30 respectively.

As previously mentioned, longer serving or higher ranked service members may have some control over their assignments. All of the children in our sample are observed in at least one year in which their parent is junior enough that we are confident that conditional random assignment holds, but for some children there exist some years in which quasi-randomization may fail. In the remaining columns of Table 1, we split the sample by children whose parents are deemed "senior" in at least one year (columns 4-6), and those whose parents are always junior personnel (columns 7-9). Not surprisingly, service members who are always junior are less likely to have a bachelor's degree or have attended college at all, and are more likely to have a high school degree as their highest level of education. They do, however, have higher AFQT scores than those who achieve "senior" status. These always junior service members are, by construction, in military service for few years and thus experience fewer moves due to military assignments. The children of always junior service members are less likely to attend college, and have lower wage income during young adulthood.

Figure 6 shows the distribution of the age at which we first observe the child in the sample. About 18 percent of children are observed at age 0 and another 17 percent at age 1. In order to study impacts of moving and location for children in high school, we need enlisted parents who arrive in the Army with children ages 5 or older. Figure 6 shows that we have substantial numbers of such children. Appendix Table 6 shows the demographic characteristics of parents with older versus younger or newborn children when the child is first observed as a dependent of an Army enlisted person.

In Table 2, we show a tabulation of number of moves for children of elementary, high school and middle school age. The first panel in the table shows the number of moves for those children that we observe for all of ages 6-10. Twenty percent of the children do not have to move during elementary school while thirty nine percent move once and thirty four percent move twice. In the second panel of Table 2 we show a cross tab of middle school moves and high school moves for those children in the sample observed for all of ages 11-17.

C. Evidence Supporting Identification

In Table 3, we provide empirical evidence that location characteristics and probability of moving at a given age are unrelated to service member characteristics once we condition upon specialty-rank-year indicators. The dependent variables we consider are the Percent BA (percent of people with 4+ years of college) in the county, the Chetty-Hendren measure of one year of exposure to the county on a child's likelihood of enrolling in college, and the Number of Moves in Elementary of High School. We use the Chetty-Hendren estimates for children at the 25th percentile of income. In columns 1-3 each child is an observation and we consider the children at different ages. Columns 1 and 2 show that place characteristics (of assignments for five year olds) are unrelated to parent characteristics including Armed Forces Qualification Test Score (AFQT), marital status, or to child gender. Column 3 does the same for 15 year olds. Column 4 stacks all 1.1 million assignments (all ages) together and again finds no statistically significant correlations between location characteristics and family characteristics.

In columns 5 and 6 we show the lack of correlation between number of moves for 17 year olds and 5 year olds and family demographics.

Table 3B performs a similar exercise and is all run at the child*assignment level since each child is assigned to a set of different counties during their parent's years of service. Column (1) shows how much of the variation in the Chetty-Hendren measure is accounted for by our specialty*rank*year fixed effects, i.e. about 13 percent. Column (2) shows that adding parental characteristics to the model does not explain much of the additional variation. In the spirit of Altonji, Elder and Taber (2005), we note that observables explain very little of the variation in locations.

In Table 3B column (2), none of the parental demographics nor family characteristics are correlated with the Chetty-Hendren measure. Together the parent and family characteristics have an F statistic of 0.92 with a p-value of 0.53. In column In columns (3) and (4), we present results using as the outcome variable the percent of people in the county with four or more years of college (which we call percent bachelors). There is a modest negative correlation between parental education and assigned county percent bachelors. The point estimates on parental education dummies are quite small and the overall F test for the joint significance of the covariates is 3.2.

D. Where Do Military Dependents Live Relative to the Assigned Base?

For assignments within the continental US, the majority of families live off base but within the county surrounding the base. We document this fact using data from the U.S. Department of Education's (DOE) Impact Aid program. Impact Aid is provided to school districts that educate children of military personnel. As part of the administration of this aid, US DOE counts the number of children (by school district) associated with each base and whether the children live on or off base.

Figure 4 shows the numbers of children living on versus off base for the ten largest bases in 2016. More than half of the children live off base. Furthermore, none of the ten largest bases offer a Department of Defense Education Agency (DoDEA) school, meaning that the children are attending school elsewhere in the surrounding counties. Clever and Segal (2013) show that only 13 percent of military children attend a DoDEA school in a given year; most of these are at overseas bases including Germany and Japan.

Figure 5 uses the Impact Aid data to show that the majority of children associated with each base attend school in a district in the same county as the base. However, this is not universally true. Since some children are living and attending school in neighboring counties, this will be a source of measurement error which will likely downward bias our estimates of the impacts of location. (If we are mismeasuring the neighborhood characteristics and that measurement error is classicial it will create downward bias.) In the analysis section we discuss several corrections for this measurement error.

E. Empirical Strategy

As discussed above, we are interested in both the impacts of different locations (e.g., different U.S. counties or overseas versus U.S.) and the impacts of moving. We begin by describing our estimation strategy for the effects of location on child outcomes. Our identification strategy is relatively intuitive because assignment to location every three to five years is quasi-random. To examine the effect of neighborhood characteristics on young adult outcomes, we conduct our analysis at the child-age level (as opposed to the child*assignment level). We regress the outcomes for child *i* (e.g., college enrollment or earnings) on a set of right-hand side variables corresponding to the randomly assigned locations for child *i* at a given age.

In our simplest specification, we take the set of children whose location is exogenously determined by the army. We exclude observations where the child's parent is relatively high rank or has more than 10 years of service at the time of assignment. We stratify the children by single ages (0, 1, 2, …, 17) or by groups of ages, meaning pre-school (ages 0-4), elementary school (5-10), middle school (12-14), and high school (ages 15-17), and ask how much the characteristics of the assigned place impacts long run outcomes. Specifically, for any age or group of ages, we run:

$$(1) \qquad Y_i = \beta\, E * X_i + \boldsymbol{\gamma} Z_i + SRY_i + \varepsilon_i.$$

Here, Y_i is an outcome, such as college enrollment or log(earnings), and X_i refers to a key right-hand side variable related to the neighborhood in which a child lives during that age or group of ages. When considering outcomes based on college enrollment, the X variables on which we focus are the Chetty-Hendren college measure and the percent of the adult population in the county with a BA (percentBA). Following Chetty-Hendren, we multiply X by the years of exposure to the place (E). This delivers an estimate of the impact of 1 year of exposure to a place with that characteristic. Finally, to compare across different locational measures (eg Percent BA, county level test scores, the Chetty Hendren measure), we standardize E*X to be mean 0 variance 1 within the sample. When considering outcomes based on earnings, the X variables on which we focus are the Chetty-Hendren income measure and the median household income in the county (med_earnings). In cases where a child is in multiple locations during say elementary school, we average the right-hand side measure weighting by the number of years in each location. The vector Z_i contains the following set of controls for family and service member background: race, gender, AFQT score, birth year, year of entry, and educational attainment. We also include child birth-year fixed effects in Z_i. The variable SRY_i is the specialty-rank-year fixed effects.

In practice, we find that estimating individual age specifications is not the most efficient method since there are thousands of specialty*rank*year effects to be estimated at each age. We find similar results with tighter standard errors when pool (stack) the data at different ages to estimate the effects at each child age all at once in a single regression:

$$(2) \quad Y_i = \Sigma_{a=0}^{17} \beta_a E_{i,a} X_{i,a} + \boldsymbol{\gamma} Z_i + SRYA_i + \varepsilon_i.$$

Children are indexed by *i* and $X_{i,a}$ refers to the key right hand side variable (e.g the Chetty-Hendren measure) at a given age, a. *SYRAi* are a full set of dummies denoting the specialty*rank*year at a child's age. In other words, we estimate the full profile of locational effects by age in a single "pooled" regression.[5] Standard errors are clustered at the child level.

The key identifying assumption in equations (1) and (2) is that conditional on the specialty and rank of the service member within a year, the right-hand side variables (e.g. the Chetty-Hendren measure or county characteristics) $X_0, \ldots, X_{17}$ are uncorrelated with characteristics of the child and the family. Our conditional random assignment checks above provide suggestive evidence that this is the case.

We use equation (2) to also consider the exposure effects of foreign assignments at various ages. To examine the impact of any foreign assignment, the variable *X* is the indicator variable *OCONUS*. We also look at the impact of specific countries: *X* includes a set of indicator variables for Germany, Italy, Japan, South Korea, the U.K., and all other foreign assignments. The comparison group in this specification contains domestic assignments.

We are also interested in the raw effects of moving at a given age. The simplest way to estimate these effects is to assume that the exact timing of an Army-induced move is uncorrelated with a child's age or family characteristics. This is a fairly plausible assumption given that the timing of a move is dictated by the sum of various shocks to when the Army had the soldier move in previous assignments. We provide evidence in Table 3 that child and family characteristics do not predict whether a child moves at a given age. This suggests running the following specifications:

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[5] In theory one could create a cross sectional regression with one observation per child. This is difficult to estimate since each child*assignment has a different speciality*rank*year control associated with it.

$$(3a)\quad Y_i = \Sigma_{a=0}^{17} \alpha_a Moved_{i,a} + \Sigma_{a=0}^{17} \delta_a X_{i,a} + \boldsymbol{\gamma} Z_i + \varepsilon_i, \text{ and}$$

$$(3b)\quad Y_i = \Sigma_{s=1}^{4} \alpha_s Moved_{i,s} + \Sigma_{s=1}^{4} \delta_s X_{i,s} + \boldsymbol{\gamma} Z_i + \varepsilon_i.$$

In equation (3a), $Moved_a$ is an indicator variable that equals one if a child moved at age a, and $X_{i,a}$ are neighborhood characteristics that a child is exposed to at age a. In addition to the same demographic characteristics contained in Equation (1), the vector Z_i also includes a set of indicator variables for the variables $Moved_a$ and X_a being missing. The former will be missing in years when the child's parent is not enlisted, and the latter will be additionally missing in years when the child's parent is stationed outside of the U.S., or to a location without neighborhood characteristics data. We conduct this analysis at the one observation per child level, rather than the child-age level. This regression thus estimates the effect of a move at a particular age, controlling for the effects of earlier and later moves along with the history of neighborhood characteristics to which a child is exposed throughout her childhood. Equation (3b) is the analogous regression when considering moves at our four child-age categories of interest.

A slightly different way to estimate the effects of moving is to compare movers to stayers within each of our four child-age categories. For this analysis, we rely on the fact that by the nature of the quasi-randomization a subset of families do not move for 5-6 years. The comparison here is between the children who move during that group of ages to children who do not. A minority of children may not move for a couple of reasons. First, some service members may have an initial term length (e.g., 4 years) that does not require multiple moves. Second, some personnel move just before a child's middle school or high school years and receive a long assignment. This enables the child to have an uninterrupted period of 3 or 4 years in middle or high school. These non-movers are the comparison group that allows us to identify the effect of moving on child outcomes. We compare children who moved during elementary school to the random subset of children who did not move during elementary school.

As a third strategy, we assume that child age is uncorrelated with the roughly three-year cycle in which the family has to move. Thus, some children are forced to move their freshman year of high school while others have to move their senior year of high school. This enables us to identify the relative impact of moving at one specific age versus another within age group. For example, we restrict our sample to the set of children who move at some point during their middle school years and estimate Equation (3), where *a* takes on the values 11, …, 13 only. We can do this for each of the four age groups that we consider.

A final way to estimate the effects of moving is to include family fixed effects and identify the effects of moving from the different ages of the children in the family. We plan to perform this analysis in the next draft of the paper.

IV. **Results**

We begin with our results on the effects of moving. Table 4 and Figure 9 show effects of moving at a given age on the probability of college enrollment estimated using Equation (3b). We have grouped child ages (roughly corresponding to pre-school, elementary, middle, high school) to increase statistical power. The right-hand side variable is a dummy for having moved one or more times during an age group.

Pre-school moves appears to be slightly positive for college enrollment while the negative effects of moving increase as a child progresses through school. Moving during elementary school has negative impacts of about .4 percentage points on the likelihood of college enrollment. This worsens to negative two percentage points for moving during Middle School and almost negative 3 percentage points for moving during high school. The sample mean for "any enrollment" is 49 percentage points; the negative impacts of moving are moderate in size but statistically and economically meaningful.

Figure 10 switches to equation (3a) and estimates, for each child age, the effects of moving on college enrollment. Again we see no effect (or maybe a slight positive effect) from moving during ages 0-5. The effects from moving become more negative as a student's career progresses. Moving at age 13 or 14 reduces college enrollment by 2 percentage points and moving at age 17 is more negative though the additional decline is not statistically significant.

In Figure 11 we switch the outcome to having 4 years of college enrollments (as recorded in Forms 1098-T). The negative impacts from moving at older ages are statistically significant though not quite as large as the impacts on "any enrollment." Moving during Middle or High School reduces enrollment for four years by 2 percentage points. The mean of this outcome in the whole sample is 18 percentage points, so on a relative basis these effects are larger than the effects on "any enrollment."

A natural question is whether the effects of moving vary meaningful by race, gender, parental AFQT score etc. Our investigations of treatment effect heterogeneity suggest that moving effects are fairly constant across demographic groups. In Appendix Figures 1 and 2 we split the sample by male and female children. We find similar impacts of moving on college enrollment for both girls and boys. In results not shown, we find similar impacts of moving for children of black and non-black parents, and children of parents with above and below median AFQT scores.

Figure 12 shows the effects of moving on log earnings at age 30. Elementary school moves are not particularly harmful to earnings, but the negative effects of moving may increase with child age. Moving during ages 15 and 16 appears to depress earnings by about 5 percentage points. Given the volatility of the individual age estimates and the lack of precision, it's difficult to be confident in our estimate of negative 5 percentage points. The evidence on wage effects from moving in high school is suggestive and is consistent with the large negative effects on college going from these same moves.

We also estimate the effects of a child spending time overseas. Figure 2 shows that most of these overseas assignments are in Europe and Japan. The effects of overseas assignment are shown in Figures 21-25. In Figure 21, we see that overseas assignments during high school raise enrollment for four plus years of college by about .5 percentage points, though this effect is not statistically significant.

Overseas assignments during middle and high school have large (in the point estimates) impacts on wages. For students who experience such an assignment, wages at age 30 rise by 4 percentage points (Figure 23). Figure 24 shows that estimated wage effects from assignment to Germany are particularly large and seem to increase with child age. Part of the OCONUS effect could stem from positive effects from being in a DoDEA school. The few studies on DoDEA schools find that their students are particularly high achieving and suggest that the schools may have high value added (Bridglall and Gordon 2003). DoDEA schools score significantly above the national average on the NAEP (despite having a high percentage of free and reduced lunch students) and the black-white test score gap within DoDEA schools is half of the national average (Smrekar Guthrie Owens and Sims 2001).

Impacts of Location Within the U.S.

We turn now to the effects of randomly assigned locations within the US. We use county level measures on the right-hand side; as detailed above most military personnel with kids live within the same county as the base but not necessarily on base.

Our research question is similar to that of Chetty and Hendren 2015 and the Moving to Opportunity Experiment (Katz, Kling, and Liebman 2004 and Chetty, Hendren, and Katz 2016). Specifically, we ask how much a year of exposure to a different location raises a child's college enrollment and earnings. There are numerous possible county measures we could put on the right-hand side and we have tried many including the percent of people over age 25 with four or more years of college, the percent of people with a high school diploma, median income, the percent of people above the poverty line, percent non-white, and average student test scores in the county.[6]

All of these measures are correlated with child's college enrollment. Our key finding is that the most useful predictors are the Chetty-Hendren prediction of a county's causal impact on college enrollment and the percentage of people in the county with a bachelor's degree. We use the Chetty-Hendren measure for families at the 25th percentile of income which may not be the most accurate for enlisted personnel but is likely more accurate than the 75th percentile of family income, the other available data.

In Figure 14A we show that the Chetty Hendren measure of a county's causal impact for a year of exposure is a strong predictor of whether a child enrolls in college. In our data the impacts of place rise monotonically with child age. Assignments at age 0-5 have a coefficient of about .10 and this rises to .4 by ages 16 or 17. A coefficient of 1 would suggest that the Chetty Hendren measure predicts college enrollment with the same slope found in their larger data set of movers.

There are numerous reasons why the children in our sample might see smaller impacts than the Chetty Hendren predicted causal effect. Our children are in military families which move

[6] Our test score measure is from the Riordan 2016 data set which standardizes county level test scores to be comparable across U.S. States. We focus on math scores but have found similar results for reading scores.

frequently. The family's children may be less immersed in any given community or county. People may invest less in social capital and relationships if they know they are temporary residents. Since the families have a support network of military families, they may less integrated into civilian life in the county. Similarly, military families and support programs and structures may mitigate the effects of any given area.

Importantly we assigned children to the county which contains the base of their parent's assignment. However Appendix Table 5 suggests that only about 80% of children attend school in the same county as their base. In Appendix Table 7 we explore a simple correction for this measurement problem. For the 41 largest bases we used the Impact Aid data to calculate a Chetty Hendren measure that is weighted by the counties where children from that base actually attend school. We regressed this more sophisticated measure on the simple county of the base measure we use in the main analysis. This is shown in Column (2) and the coefficient on the simple measure is .9. This suggests that we may want to scale up our estimates of the Chetty Hendren measure by dividing by .9.

Finally the Chetty Hendren measures could overstate county impacts if there is selection into moving which is not fully accounted for in their procedure. In future results we will explore whether our estimates rise when we do not control for selection or examine our sample after leaving the Army.

In Figure 13A-13C we regress college going on the Percent BA in the county where the family is assigned. Percent BA is standardized to mean zero variance one and these effects are for one year of exposure. County percent BA during pre-school does not affect college enrollment. However the size of the effect grows during middle and high school. By age 16, one year's exposure to a county with a 1 standard deviation higher percent BA raises college going by .5 percentage points. The estimates suggest that 10 years of exposure from ages 7-16 would raise college going by 5 percentage points. We add up the effects over ages 7-16 and report the results in Table 9.

Figure 14B performs the same exercise for the Chetty Hendren college going measure where we have standardized the measure to have variance 1. One year of exposure to a county with a one standard deviation higher Chetty Hendren measure raises college going by .6 percentage points. Figures 15 and 16 use as the right hand side the percentage of residents with family income that is

150 percent or more of the poverty line (Figure 15) and the county's grade 3-8 math score percentile in the national distribution. All measures are standardized.

Most of these figures show a pattern of effects which increase with student age. Assignment during high school to a county with residents who are 1 standard deviation above the national fraction "non-poverty" raises college enrollment by .5 percentage points for each year of exposure. 10 years of exposure from 7-16 is estimated to raise college enrollment by 5 percentage points. Exposure to counties with higher math scores shows a similar pattern and similar sized effects. At age 16 one year of exposure would raise college enrollment by about .4 percentage points. (This is reported in Table 8.)

We turn now to estimated wage impacts of place. In Figure 17 the right hand side variable is the county's Percent BA (standardized) *years of exposure. The dependent variable is log(wages) at age 30. One year's exposure in middle school raises wages by .5 percent and one years' exposure in high school raises wages by 2 percentage points. Figure 19 shows an analogous regression in which the right hand side variable is county median earnings (standardized) times years of exposure. Again impacts are larger at older ages and a year of exposure to a county with one standard deviation higher on county median earnings raises own earnings by 2 percentage points. These are clearly large impacts and suggest that spending all of high school in such a county would raise earnings by 8 percentage points.

In Table 8 we provide a summary of the impacts of six different right hand side measures (all standardized and expressed as a year's worth of exposure) on college enrollment, log(wages at 30), percentile of wages at 30, and median income in home zip code at age 30. Assignment to counties with more desirable characteristics raises both college going and earnings at age 30 by large amounts. A year of exposure at age 16 to a county with one standard deviation more bachelor's degrees (a four percentage point rise) raises own college enrollment by .66 percentage points. The same year of exposure is associated with a 3 percent increase in log wages at age 30. If we measure county quality by median earnings or the Chetty Hendren impact on college going, we find similar effects on wages and college going.

V. Conclusion

Social scientists have put a great deal of effort into understanding the determinants of young adult outcomes. We tackle this longstanding question with a data set of children who experience random shocks to their location and the timing of their moves. Using this novel source of identification, our results confirm and clarify much of the existing literature.

Specifically we find that moving causes significant amounts of disruption and that these effects are long lasting. Moving in high school is significantly worse for college enrollment and earnings than moving in middle school, which in turn is significantly worse than moving in elementary school. Moving in high school lowers college enrollment rates by 2-3 percentage points. Furthermore, moving in high school lowers earnings at ages 25 and 30 by about 3 percentage points. The negative earnings effects are too large to be attributable purely to returns to college. Consider that not all students who enroll will receive a BA. Even if the BA rate fell by 3 percentage points, a 5 percentage point reduction in earnings would imply a 166 return to BA relative to a high school diploma. In other words, our results suggest there are important channels to earnings effects other than the impact via post-secondary degree attainment.

Time spent overseas as a child appears to be beneficial for earnings at age 30. The largest positive effects (5 percent increases in earnings) occur for time spent out of the US during middle and high school ages, i.e. 10-17. This is plausible in that middle and high school children may be old enough to experience the benefits of living in another culture.

Across US counties, we find support for the Chetty Hendren measures of the impact of a county on future college enrollment and earning. One year of exposure to a county predicted to increase college going raises the college enrollment of military children by about .4 percentage points. Our confidence intervals do rule out the Chetty Hendren point estimates. However there are plausible reasons to think that military dependents may absorb fewer effects from their locale; military dependents know they are temporary residents and they may also have their own informal network of other military dependents. Our point estimates suggest that a year of exposure to a county has a larger effect on college going when that exposure occurs later in a students' career.

Overall we find evidence that moving and location has profound impacts on young adult outcomes. A single move can depress earnings or college enrollment by 3 percentage points. Ten years' worth of exposure to a county associated with high college enrollment can raise college enrollment by 5 percentage points.

At least three distinctive patterns emerge in our results. First, effects appear to be larger for older students. Second the impacts on earnings (from location in high school) impact earnings much more than we would have expected given the moderate impacts on college enrollment. Third the patterns of results are similar across gender, race and groups of parental AFQT score.

From a policy perspective, the Army might consider revising its assignment process in ways that capitalize on the benefits of certain areas for certain families, with the likelihood that this might increase retention and productivity. We hope these results contribute to a more complete picture of the importance of environmental shifts and how these impacts vary by child age.

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Table 1: Summary Statistics

	All Observations			Ever senior= 1			Ever senior= 0		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Variable									
Panel A: Demographic Characteristics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AFQT score	54.14	20.05	598,791	52.98	20.53	383,518	56.21	18.99	215,273
High school dropout	0	0.05	598,791	0.00	0.03	383,518	0.01	0.07	215,273
Completed GED	0.06	0.23	598,791	0.05	0.21	383,518	0.07	0.26	215,273
High school graduate	0.51	0.5	598,791	0.40	0.49	383,518	0.69	0.46	215,273
Associate's degree	0.1	0.3	598,791	0.13	0.34	383,518	0.04	0.20	215,273
Some college	0.26	0.44	598,791	0.33	0.47	383,518	0.14	0.35	215,273
College degree	0.06	0.24	598,791	0.o7	0.26	383,518	0.04	0.19	215,273
Graduate degree	0.01	0.11	598,791	0.02	0.12	383,518	0.00	0.07	215,273
Male	0.92	0.28	598,791	0.94	0.23	383,518	0.87	0.34	215,273
Child = male	0.51	0.5	598,791	0.50	0.50	383,518	0.51	0.50	215,273
Ever married	0.17	0.37	598,791	0.16	0.37	383,518	0.18	0.39	215,273
Black	0.35	0.48	598,791	0.38	0.49	383,518	0.31	0.46	215,273
White	0.5	0.5	598,791	0.47	0.50	383,518	0.55	0.50	215,273
Hispanic	0.08	0.27	598,791	0.08	0.27	383,518	0.09	0.28	215,273
Other race	0.07	0.25	598,791	0.07	0.26	383,518	0.06	0.24	215,273
Panel B: Military Moves									
Number of moves, ages 0-17	2.31	1.47	598,791	2.70	1.51	383,518	1.63	0.97	215,273
Any move, pre-school	0.46	0.5	598,791	0.46	0.50	383,518	0.45	0.50	215,273
Any move, elementary school	0.61	0.49	598,791	0.69	0.46	383,518	0.46	0.50	215,273
Any move, middle school	0.39	0.49	598,791	0.48	0.50	383,518	0.22	0.42	215,273
Any move, high school	0.36	0.48	598,791	0.45	0.50	383,518	0.22	0.41	215,273
Ever OCONUS	0.57	0.49	598,791	0.70	0.46	383,518	0.35	0.48	215,273
Years in military sample	6.63	3.83	598,791	7.56	3.99	383,518	4.98	2.86	215,273
Panel C: Tax Based Outcome Variables									
Ever college	0.49	0.5	598,791	0.51	0.50	383,518	0.45	0.50	215,273
College, 4-years or more	0.18	0.39	487,622	0.20	0.40	333,049	0.15	0.36	154,573
Wage and salary income, age 25	16,871	15,062	275,141	17,373	15,143	211,791	15,193	14,663	63,350
Wage and salary income, age 30	23,412	21,893	152,111	24,060	22,099	126,833	20,161	20,528	25,278

Table 2

Cross Tabs of Moves by Child Age

Number of Elementary School Moves

Elementary Moves	Freq.	Percent
0	14,252	20.08
1	27,404	38.6
2	24,242	34.15
3	4,905	6.91
4	186	0.26
Total	70,989	100

Number of Middle School and High School Moves

	High School Moves					
Middle School Moves	0	1	2	3	4	Total
0	3,948	1,859	739	41	1	6,588
1	2,945	3,590	853	33	0	7,421
2	744	588	105	3	0	1,440
3	11	3	1	0	0	15
Total	7,648	6,040	1,698	77	1	15,464

Table 3
Checks for Conditional Random Assignment…At Child Age Level

	(1)	(2)	(3)	(4)	(5)	(6)
	Percent BA in County	**Chetty Hendren College Going Effect**	**Chetty Hendren College Going Effect**	**Chetty Hendren College Going Effect**	**Number of High School Moves**	**Number of Elementary Moves**
	Assigns for Five Year Olds	5 Year Olds	15 Year Olds	All Assignments	17 Year Olds	5 Year Olds
Parents AFQSC	2.76E-05	-0.000427	-0.000239	0.000203	-0.00298	0.000621
	-4.29E-05	-0.0005	-0.00239	-0.000221	-0.0068	-0.00154
AFQT1	-0.0102	-0.182	-0.117	-0.0147	0.234	-0.0696
	-0.0115	-0.181	-0.363	-0.0597	-0.505	-0.162
AFQT2	-0.00743	-0.198	-0.063	-0.0221	0.0238	-0.0259
	-0.0116	-0.178	-0.365	-0.0612	-0.428	-0.137
AFQT3a	-0.0075	-0.21	-0.0833	-0.0194	-0.0807	-0.0422
	-0.0112	-0.176	-0.342	-0.0605	-0.276	-0.13
AFQT3b	-0.00805	-0.229	-0.0884	-0.021	-0.13	-0.0705
	-0.0111	-0.177	-0.339	-0.061	-0.174	-0.121
AFQT4	-0.00621	-0.23	-0.0698	-0.0193		-0.0886
	-0.0109	-0.182	-0.314	-0.0612		-0.135
Black	0.000289	-0.00474	0.00996	-0.00944	0.0989	0.0408**
	-0.00256	-0.0293	-0.0309	-0.0255	-0.0731	-0.02
Hispanic	-0.00162	0.0267	0.0719*	0.0168	-0.0555	0.0416
	-0.00225	-0.0252	-0.0419	-0.0177	-0.11	-0.0272
Parents Ever Married	0.000143	0.0041	0.0453**	0.00256	0.0151	0.136***
	-0.000993	-0.00821	-0.0227	-0.00587	-0.0869	-0.0269
Child (Male)	-0.000185	-0.00454	-0.0197	0.00136	0.0532	-0.0104
	-0.000324	-0.00407	-0.0176	-0.000876	-0.0748	-0.0143
F Test	1.55	1.42	1.23	0.78	0.81	5.03
P Value	0.13	0.18	0.28	0.66	0.6	0
Observations	60,164	68,444	10,668	1,137,389	2,523	11,300
R-squared	0.286	0.274	0.529	0.128	0.671	0.447

Table 3B
Checks for Conditional Random Assignment

	Chetty-Hendren College Effect		Percent BA in the County		Percent BA in State		Median Income in State	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	FE	FE+Covariates	FE	FE+Covariates	FE	FE+Covariates	FE	FE+Covariates
Child Age		-0.0004		0		0		0.0642
		(0.0005)		0		0		(2.4104)
Male		0.017		-0.0025**		-0.0006		-123.8424
		(0.0158)		(0.0012)		(0.0006)		(96.8354)
Black		-0.0054		0.0009		0		27.9874
		(0.025)		(0.0018)		(0.0016)		(111.4878)
Hispanic		0.0172		-0.0006		0.0015		1.2981
		(0.0181)		(0.0018)		(0.0013)		{105.1790)
Other Race		0.0028		0.0029		0.0030*		143.1304
		(0.0125)		(0.0024)		(0.0015)		(110.7812)
Parents AFQSC		0.0002		0.0000*		0.0000**		2.2446**
		(0.0002)		0		0		(0.9021)
High School Dropout		-0.0107		-0.0034**		-0.0015		-209.5986**
		(0.0271)		(0.0014)		(0.0009)		(105.6491)
High School Graduate		0		-0.0034***		-0.0013**		-205.0850**
		(0.0221)		(0.0013)		(0.0006)		(84.8279)
Some College		0.0056		-0.0030***		-0.0012**		-183.0245***
		(0.0152)		(0.001)		(0.0006)		(69.1635}
College		0.008		-0.0030***		-0.0010**		-132.5368**
		(0.0159)		(0.001)		(0.0004)		(55.8365)
Parents Ever Married		-0.0002		-0.0010*		-0.0002		-86.6634**
		(0.0072)		(0.0006)		(0.0003)		(36 .4686)
Parents # of Dependents		-0.0028		-0.0002		0		0.3701
		(0.0027)		(0.0002)		(0.0001)		(13.3638)
Observations	1,495,693	1,495,693	1,315,032	1,315,032	1,495,693	1,495,693	1,495,693	1,495,693
R-squared	0.1247	0.125	0.1313	0.1324	0.0876	0.0886	0.0876	0.1320
Adjusted-R2	0.1072	0.1075	0.1117	0.1129	0.0694	0.0704	0.0694	0.114660
Outcome mean	-0.0434	-0.0434	0.1605	0.1605	0.1709	0.1709	0.1709	31236.000000
Joint-F-stat		0.9205		3.2833		1.2007		3.639892
Joint-p-value		0.5269		0.0002		0.2825		0.000046

Table 4
Effects of Moving

VARIABLES	(1) College	(2) College, 4+ years	(3) Log (wages, 25)	(4) Log (wages, 30)
Moved				
Pre-school	0.004	0.015***	0.032*	
	(0.003)	(0.002)	(0.019)	
Elementary school	-0.004*	-0.004**	0.017	-0.023
	(0.003)	(0.002)	(0.012)	(0.023)
Middle school	-0.020***	-0.008***	-0.006	0.015
	(0.003)	(0.002)	(0.011)	(0.018)
High school	-0.026***	-0.014***	-0.019	-0.028
	(0.003)	(0.002)	(0.015)	(0.022)
Observations	598752	598752	237478	125774

Table 5

Effects of Moving (Single Age Level)

	(1)	(2)	(3)	(4)
VARIABLES	College	College, 4+ years	Log (wages, 25)	Log (wages, 30)
Age 1	0.004	0.007***		
	(0.003)	(0.002)		
Age2	0.014***	0.012***	-0.022	
	(0.004)	(0.003)	(0.052)	
Age3	0.005	0.012***	0.012	
	(0.004)	(0.003)	(0.054)	
Age4	0.006*	0.005*	0.012	
	(0.004)	(0.003)	(0.030)	
Age 5	0.008**	0.004	-0.002	
	(0.004)	(0.003)	(0.022)	
Age 6	0.004	0.001	-0.006	
	(0.004)	(0.003)	(0.019)	
Age 7	0.000	-0.006**	0.006	0.088
	(0.004)	(0.003)	(0.018)	(0.061)
Age 8	-0.010***	-0.016***	-0.007	0.023
	(0.004)	(0.003)	(0.016)	(0.065)
Age9	-0.015***	-0.019***	-0.024	-0.065*
	(0.004)	(0.003)	(0.016)	(0.036)
Age 10	-0.012***	-0.015***	-0.015	-0.020
	(0.004)	(0.003)	(0.016)	(0.029)
Age 11	-0.022***	-0.017***	-0.019	-0.004
	(0.004)	(0.003)	(0.016)	(0.026)
Age 12	-0.024***	-0.016***	-0.042**	-0.021
	(0.004)	(0.003)	(0.017)	(0.026)
Age 13	-0.024***	-0.012***	-0.018	0.008
	(0.004)	(0.003)	(0.017)	(0.025)
Age 14	-0.020***	-0.011***	-0.016	-0.011
	(0.004)	(0.003)	(0.018)	(0.026)
Age 15	-0.018***	-0.012***	0.018	-0.064**
	(0.005)	(0.003)	(0.019)	(0.027)
Age 16	-0.024***	-0.018***	-0.006	-0.077***
	(0.005)	(0.003)	(0.022)	(0.030)
Age 17	-0.029***	-0.020***	-0.050**	-0.032
	(0.005)	(0.003)	(0.025)	(0.031)
Observations	598,752	598,752	237,478	125,774

Table 6

Effects of Assignment to a Base Outside the Continental US (OCONUS)

	(1) College	(2) College, 4+ years	(3) Log (wages, 25)	(4) Log (wages, 30)
OCONUS				
Pre-school	0.002	0.001	-0.003	
	(0.002)	(0.002)	(0.017)	
Elementary school	-0.002	-0.004**	-0.012	0.032
	(0.002)	(0.002)	(0.011)	(0.021)
Middle school	0.001	0.005**	-0.002	0.002
	(0.004)	(0.002)	(0.014)	(0.021)
High school	0.009**	0.005*	0.008	0.044*
	(0.004)	(0.002)	(0.018)	(0.023)
Observations	598752	598752	237478	125774

Table 7

Effects of Place Quality by Stint Level

These are the impacts for one year of exposure to a place that is 1 standard deviation higher on the measure. Each cell is from a separate regression. These constrain the effect to be the same at all ages. For separate coefficients at each age see the corresponding figures below.

	(1) College Enrollment	(2) Log (Wages) At Age 30	(3) College Enroll 4 Yrs	(4) Log (Wages) At Age 25
Percent BA in the County	0.003***	0.008	0.003***	0.008*
	(0.001)	(0.000)	(0.001)	(0.004)
Percent BA using LEAs	0.004***	-0.008	0.002***	-0.004
	(0.001)	(0.007)	(0.000)	(0.003)
Chetty Hendren College Impact	0.003***	0.011	0.001	0.003
	(0.001)	(0.008)	(0.001)	(0.004)
Median Earnings in County	0.001*	0.012	0.003***	0.008**
	(0.001)	(0.000)	(0.001)	(0.004)
Percent >150% Poverty	0.000	0.008	0.002***	0.003
	(0.001)	(0.000)	(0.000)	(0.004)
Chetty Hendren Income Impact	-0.001	0.007	-0.001	0.002
	(0.001)	(0.010)	(0.001)	(0.005)

Table 8

Summary: Impacts of Place At Age 16

These are the impacts for one year of exposure to a place that is 1 standard deviation higher on the measure. These are measure for 16 year olds.

A Year of Exposure at Age 15/16 to…	Impact of a 1 Std Change *100				
	College Going (0-1)	College Going for 4+ Years (0-1)	Log (Wages 30)	Percentile Wages at 30	Log Zip Code Income at 30
Chetty/Hendren College Measure	**0.0076**	0.0019	0.0081	0.3940	0.0026
	(0.0023)	(0.0014)	(0.0139)	(0.2901)	(0.0037)
Percent Bachelor's Degrees in County	**0.0066**	**0.0042**	**0.0343**	**0.8420**	**0.0189**
	(0.0026)	(0.0016)	(.0161)	**(.331)**	(0.0047)
Median Earnings in County	**0.0042**	**0.0052**	**0.0419**	**0.9290**	**0.0175**
	(0.0026)	(0.0016)	**(.0173)**	**(.0349)**	**(0.0044)**
Percent Above Poverty in County	0.0035	**0.0051**	0.0351	0.5511	0.0138
	(0.0028)	(0.0017)	(0.0184)	(.3756)	(0.0050)
Chetty Hendren Income Measure	-0.0017	0.0006	-0.0002	0.1670	-0.0044
	(0.0022)	(0.0014)	(0.0174)	(0.3230)	(0.0040)
Standardized Math Scores in LEAs	0.0016	**0.0042**	0.0016	-0.0167	-0.0026
	(0.0022)	(0.0016)	(0.0022)	(0.0143)	(0.0038)
Mean Dependent Variable	0.4900	0.1500	23,412	50	

Table 9

Relative Impacts on College Attendance

	Impact on College Attendance	Standard Error
Moving in High School	-0.025	0.005
Ten Years in a Place with 1 Std Higher Percent BA	0.047	0.017
Ten Years in a Place with 1 Std Higher Chetty Hendren	0.046	0.016
Having a Parent with 1 Std Better AFQT	0.004	0.001
Parent Has Some College Versus High School	0.016	0.002
Parent Has BA Versus High School	0.070	0.004
Married Parents		
Chetty Hendren Estimate 10 Years in Better Place (Whole US)	0.073	0.018
Child is Male	-0.130	0.0011

Figure 1

Base Locations US: Moves in the Sample

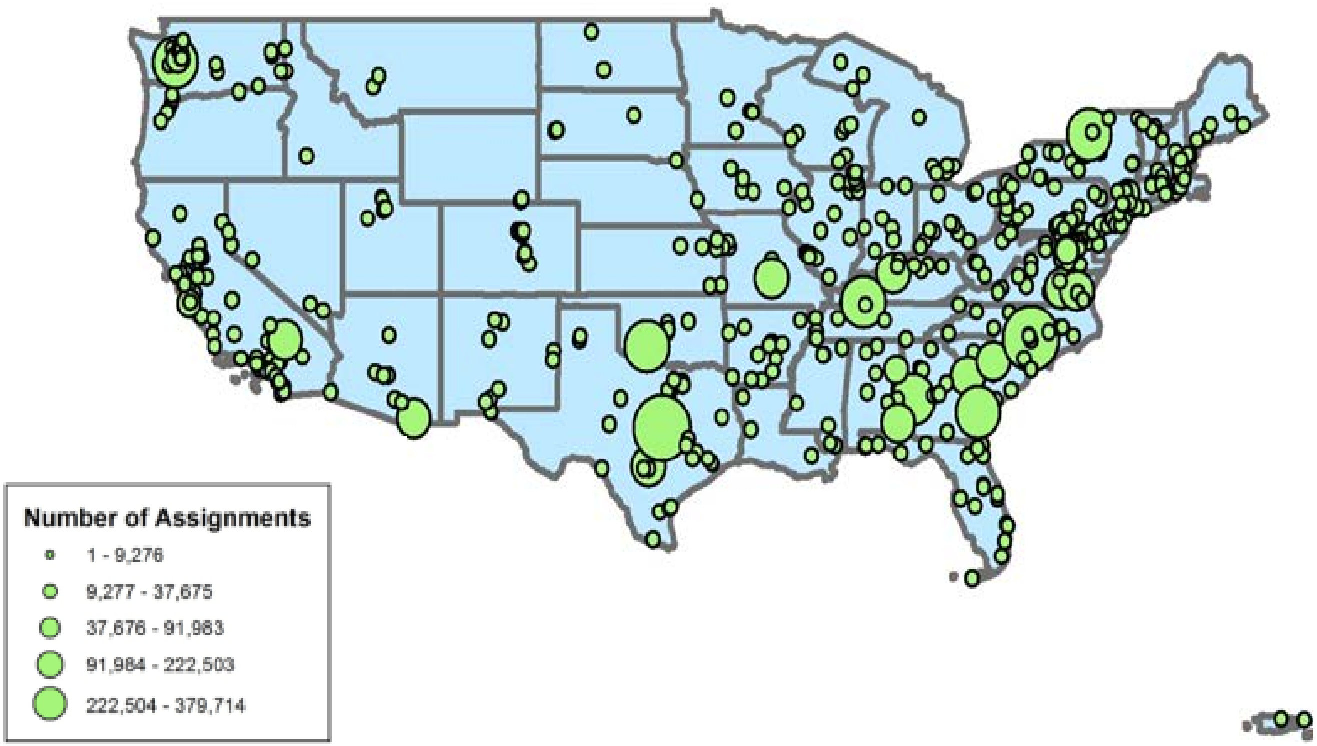


Figure 2

Locations of Army Moves in Sample: World

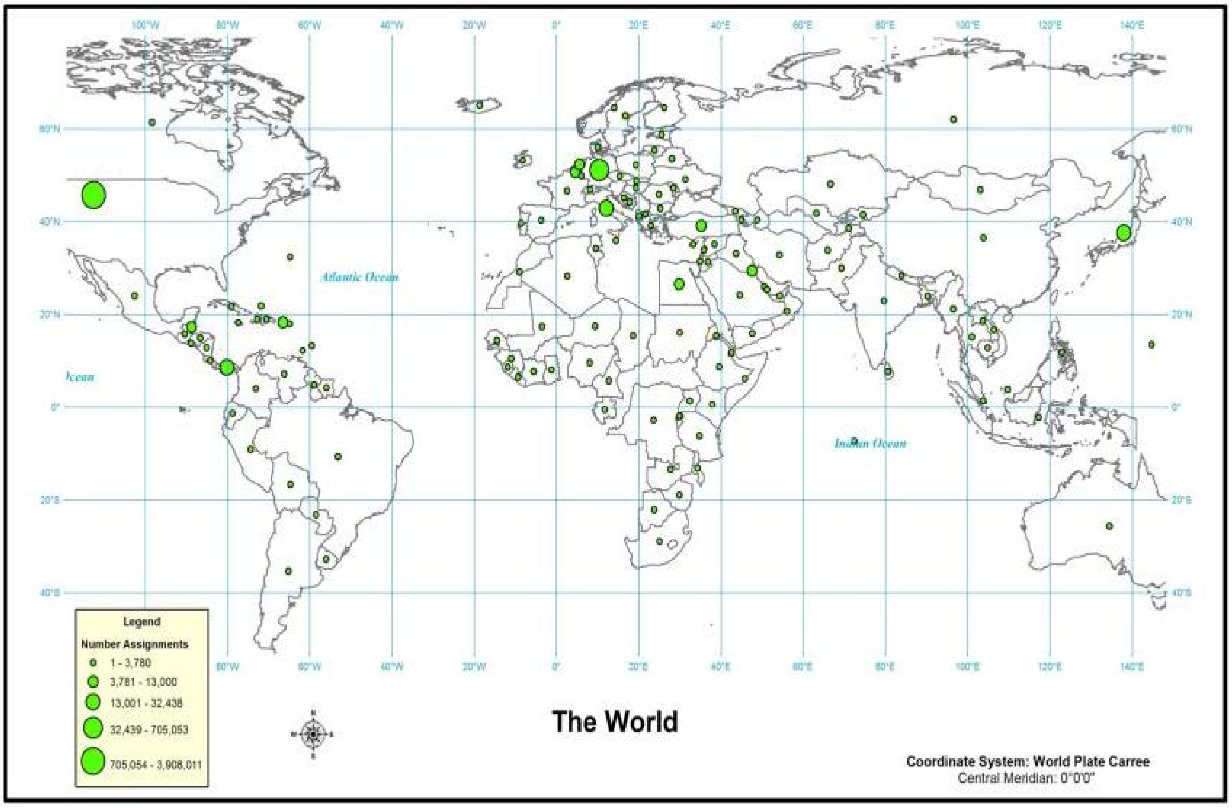


Figure 3A: FT Hood, TX

Legend
Military Kids By Zip Code
Student Count

1 - 37
38 - 112
113 - 219
220 - 421
422 - 655
656 - 1,100
1,101 - 2,063
2,064 - 20,000
State boundaries
County boundaries

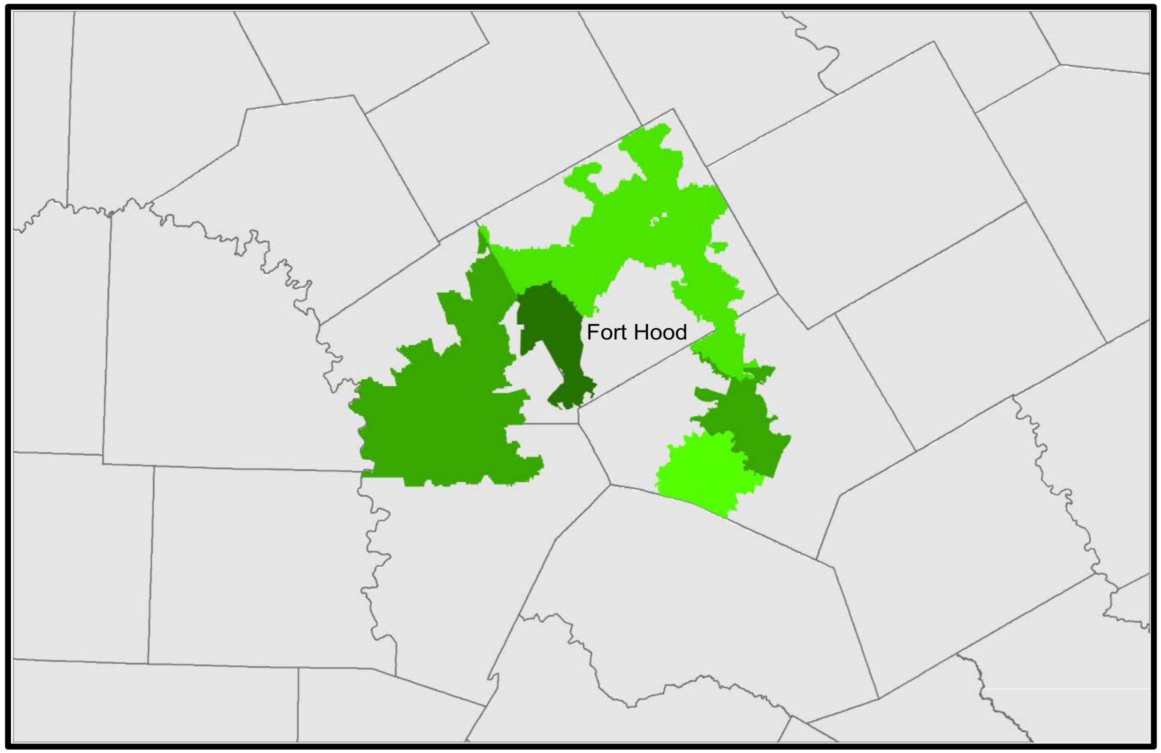


Figure 3B: Southern California

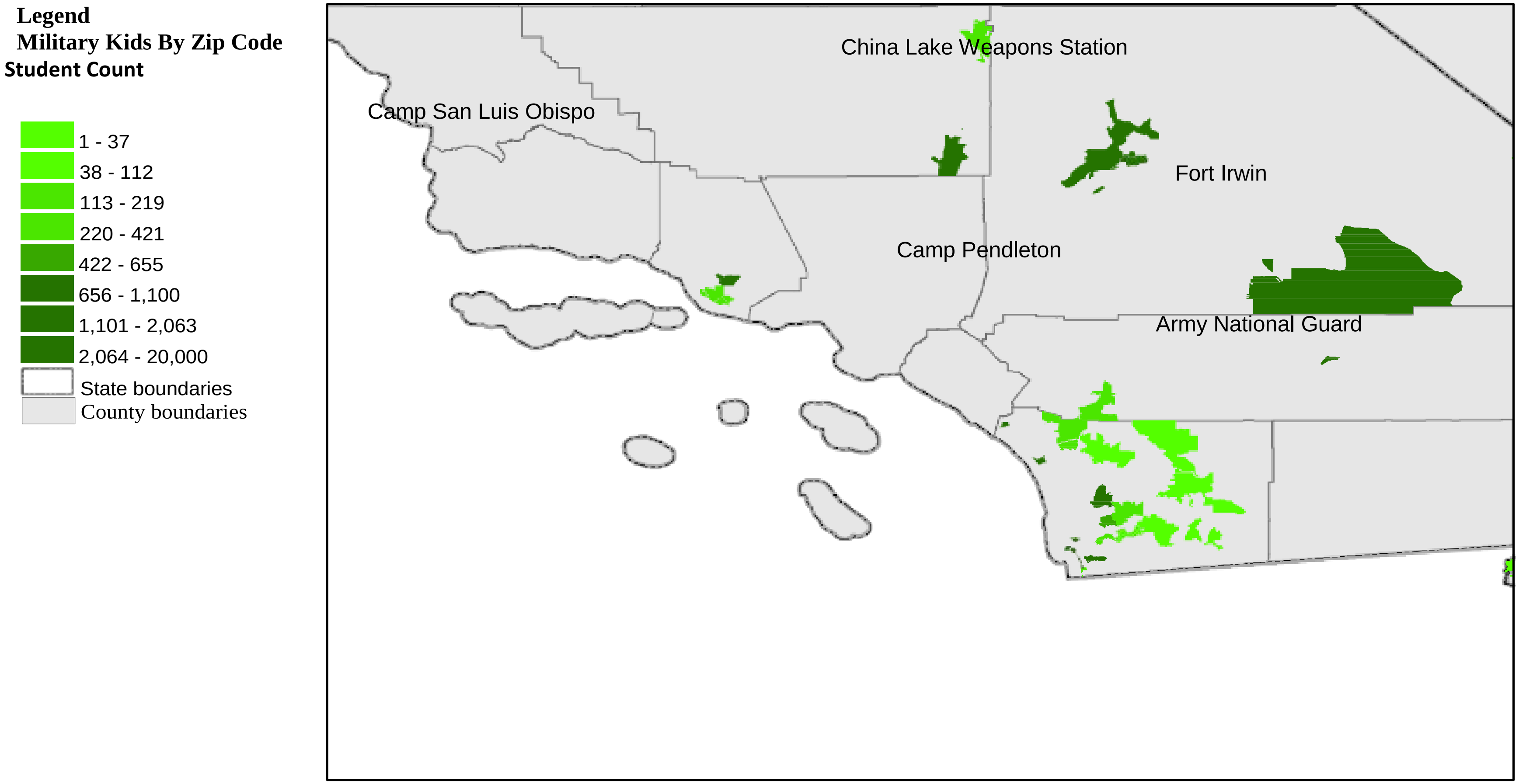


Figure 3C: Fort Drum, New York

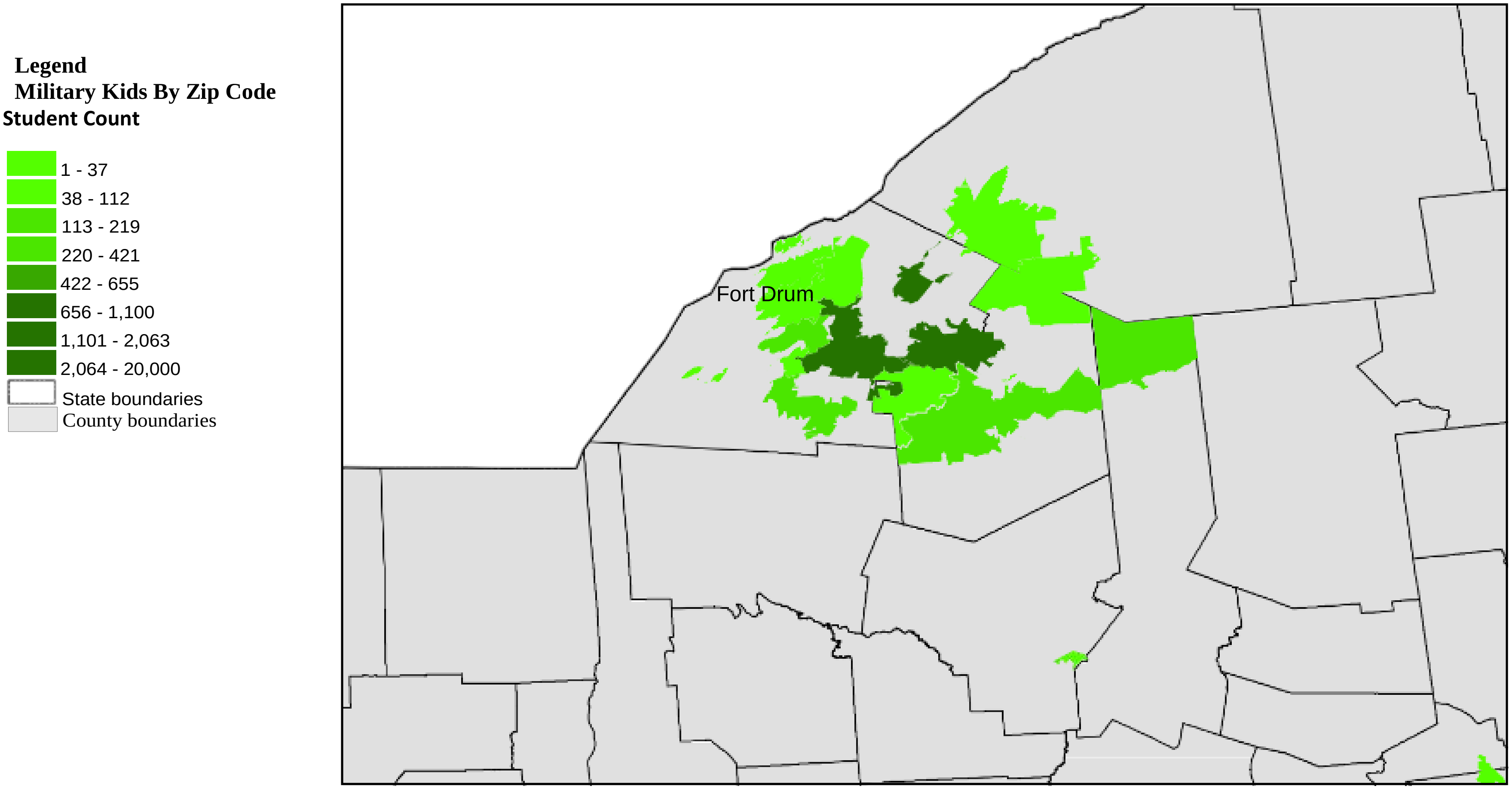


Figure 4

Live on Base Versus Off

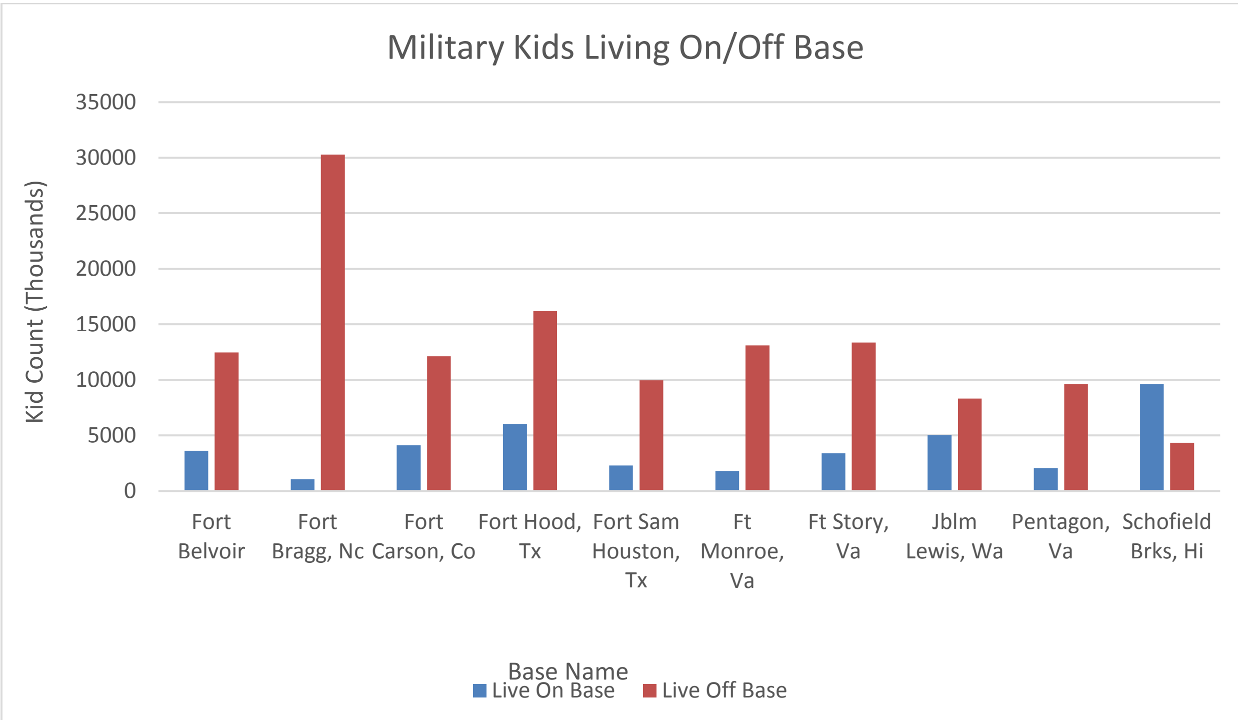


Figure 5

Attending School in County

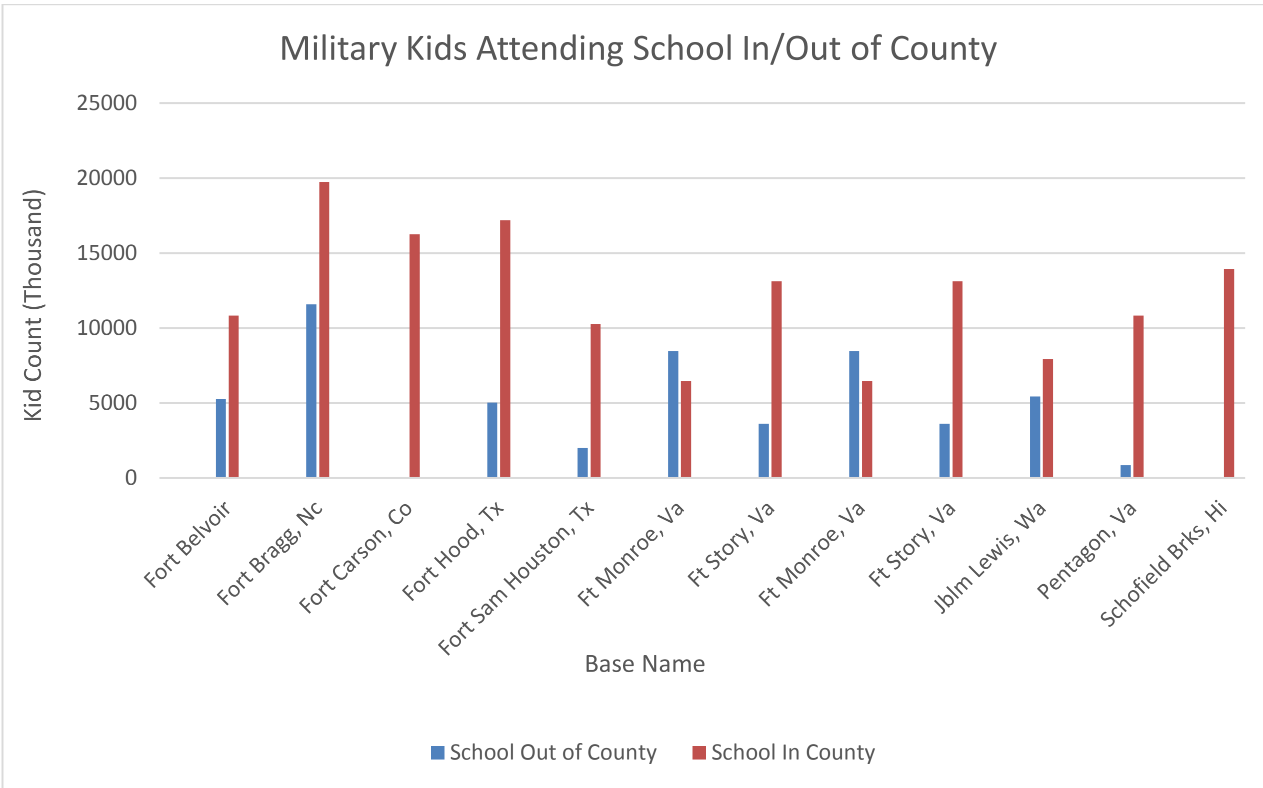


Figure 6

Age at Which We First Observe Child

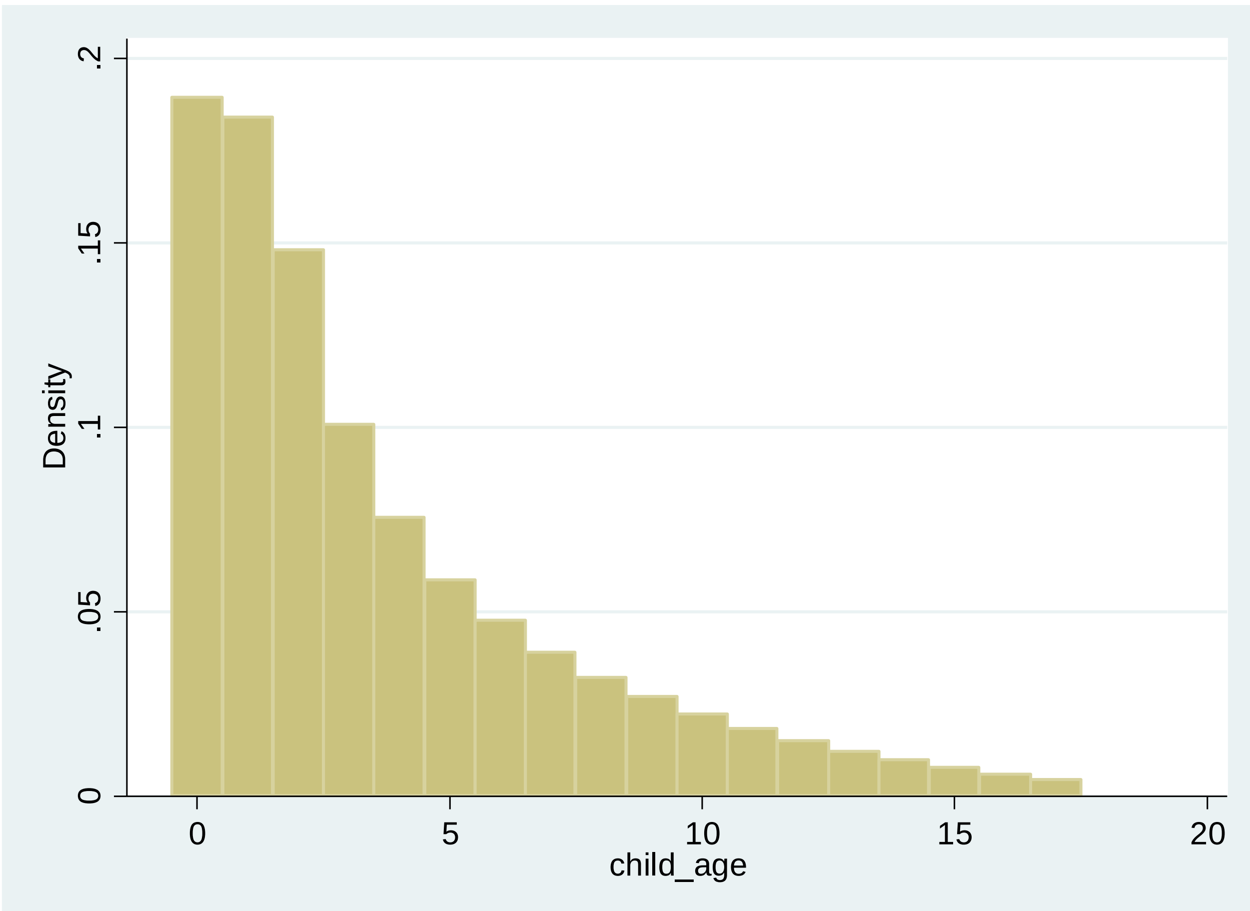


Figure 7

Number of Years for Which We Observe the Child

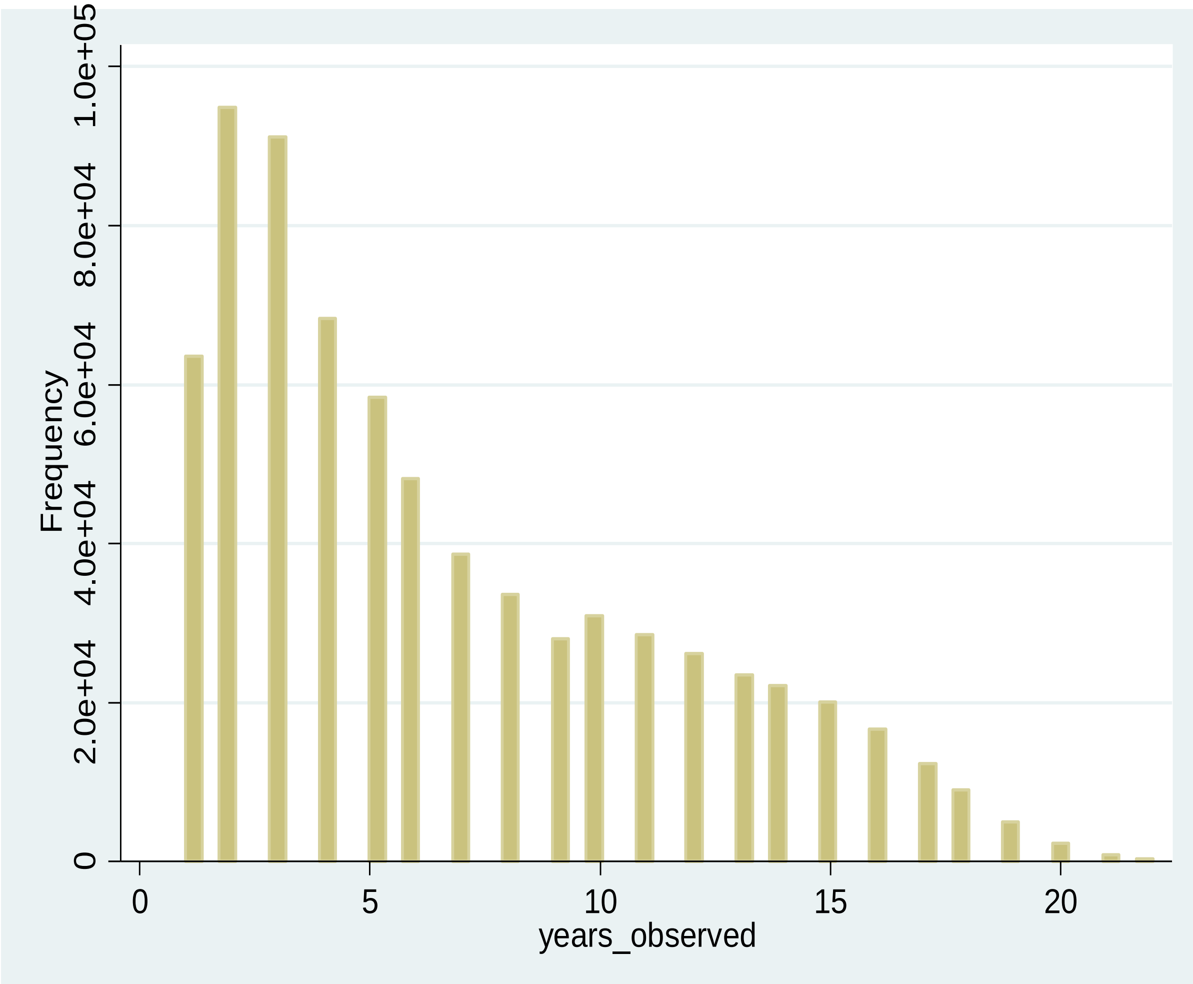


Figure 8

Histogram for Length of Stay in Days

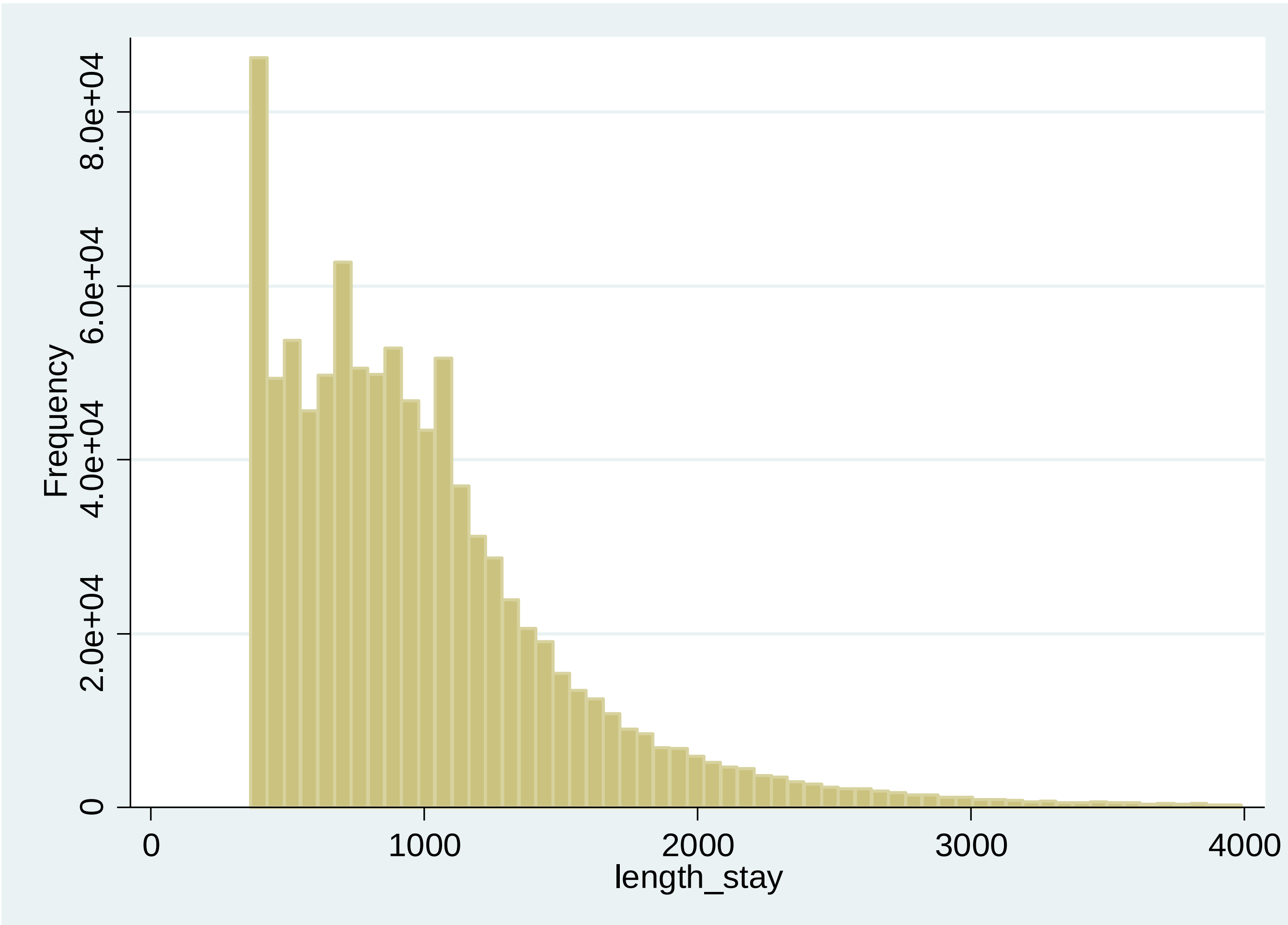


Figure 9

Impact of Moving on College Enrollment by Age Group

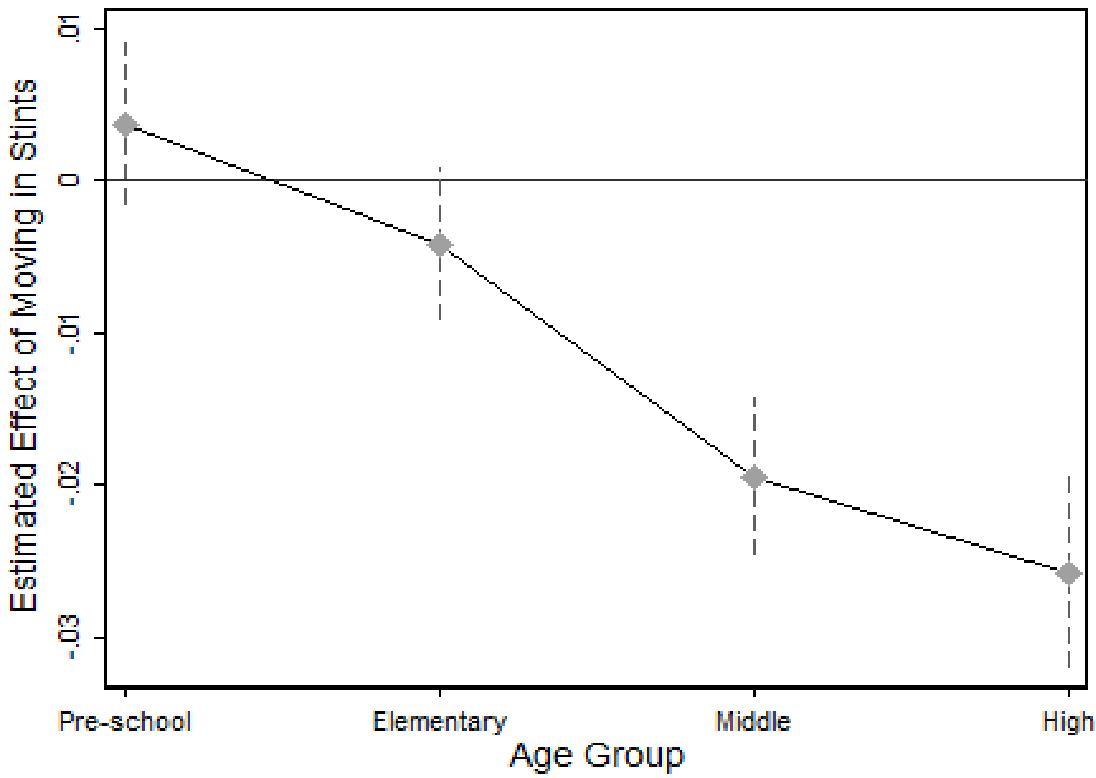


Figure 10

Impact of Moving at Each Age

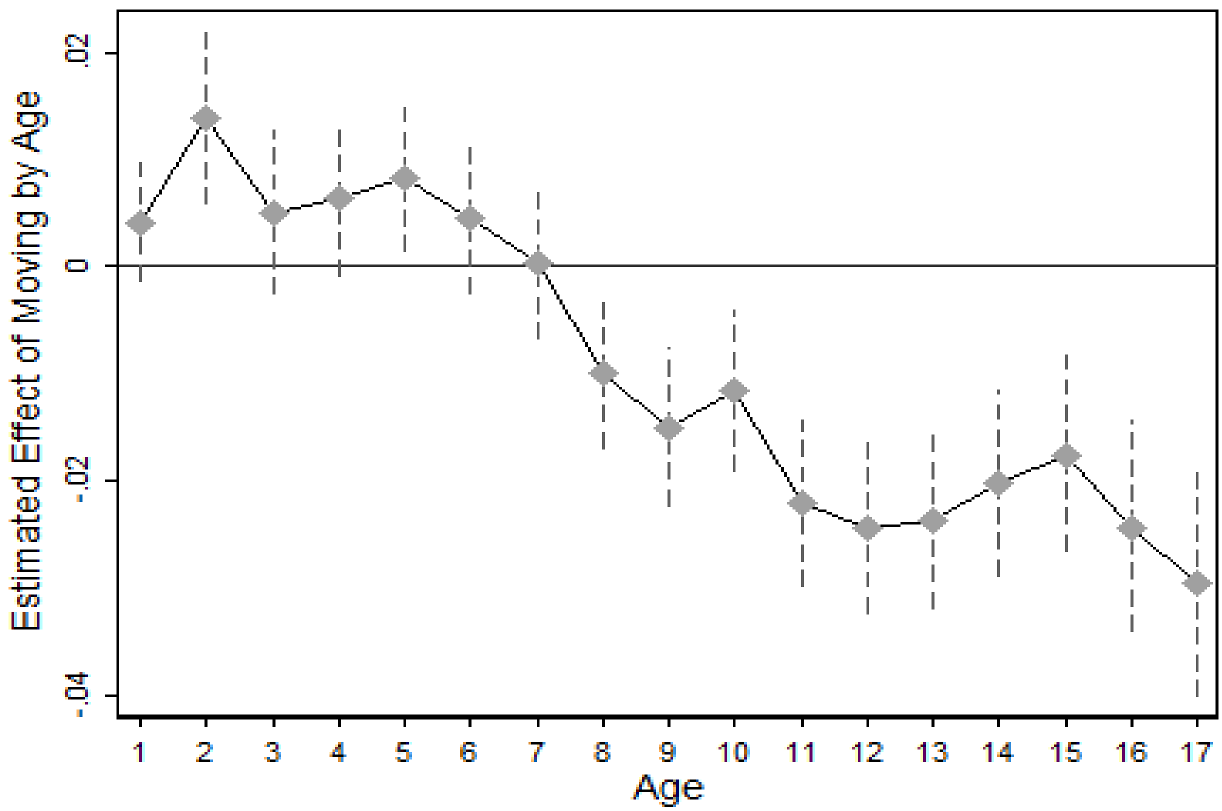


Figure 11

Impact of Moving on Enrollment for 4 Years

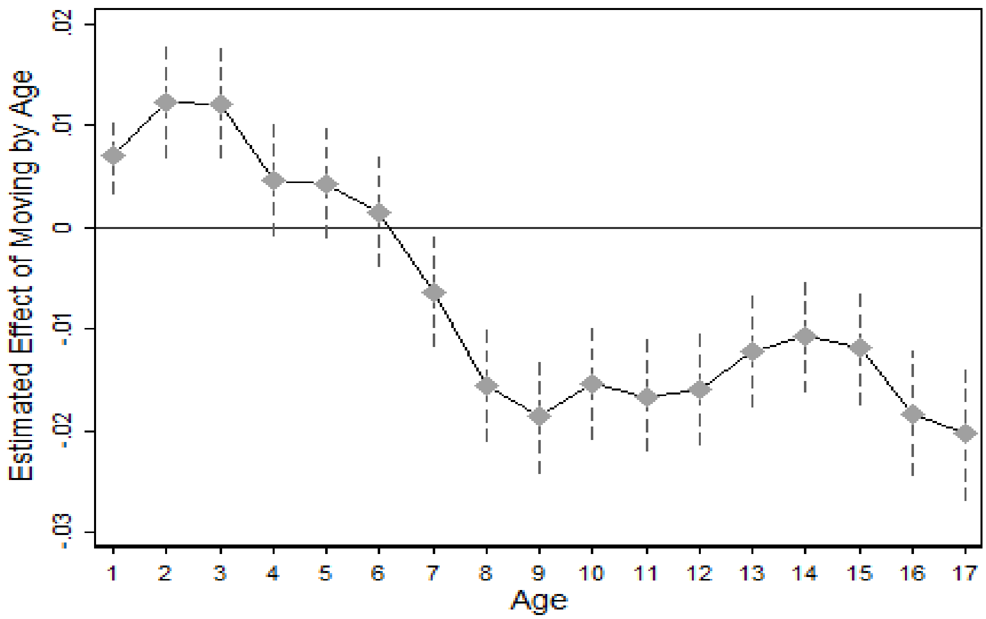


Figure 12

Impact of Moving on Log Wages at Age 30

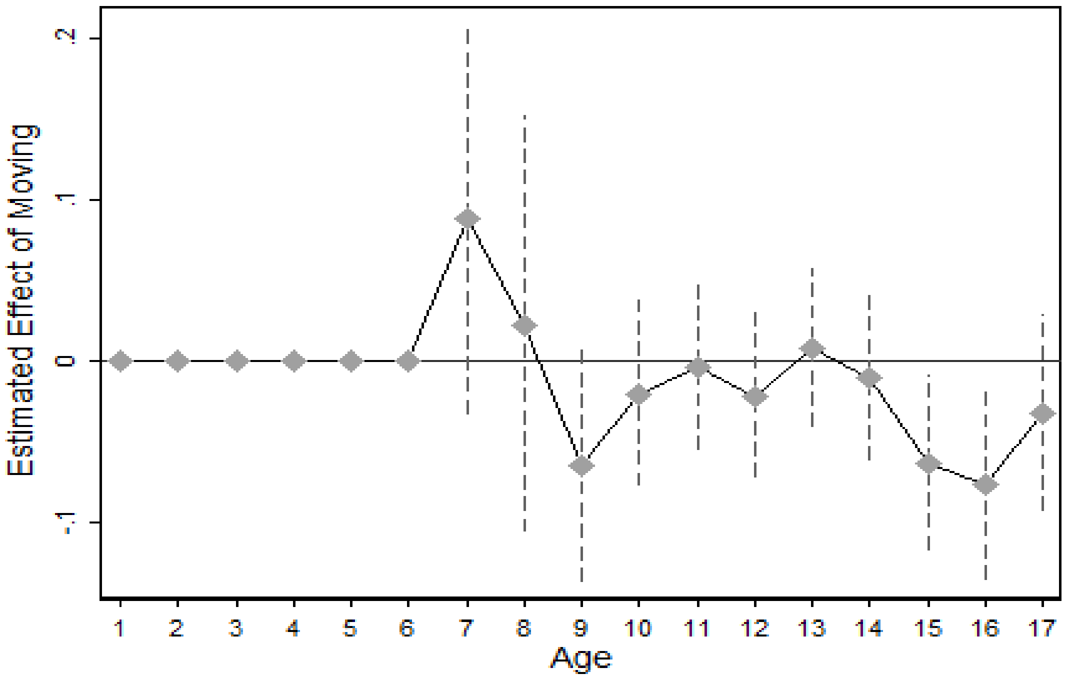


Figure 13A
Effect of County Percent BA on College Going
(Grouped Ages)

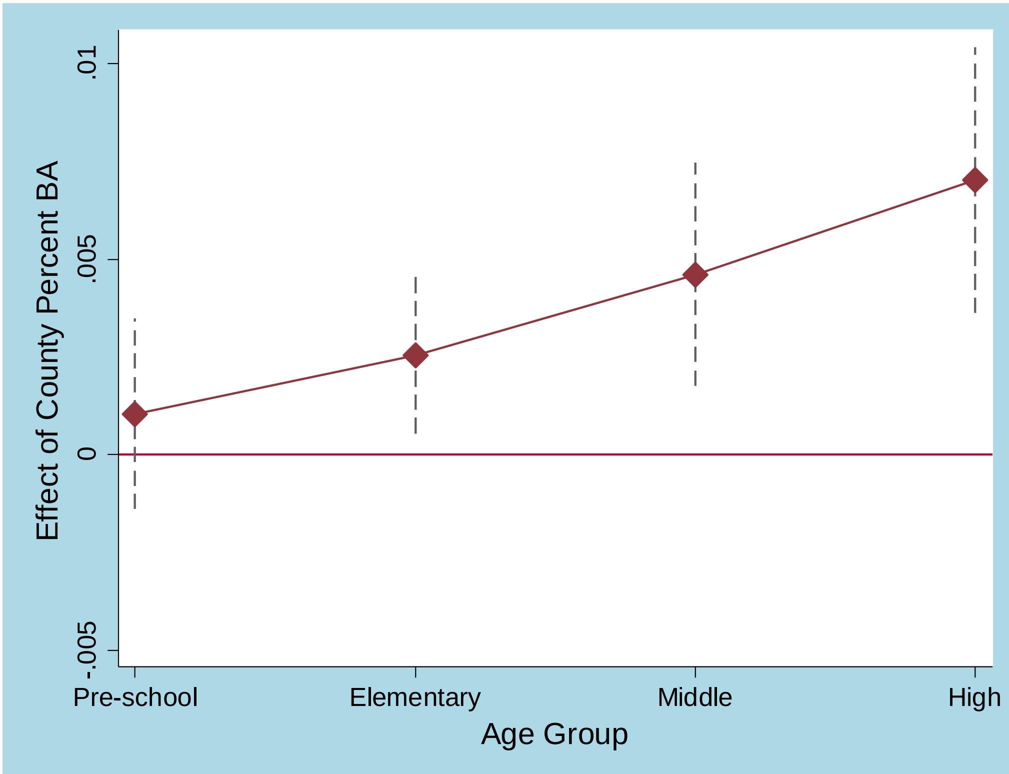


Figure 13B

Effect of County Percent BA on College Going

(Single Ages)

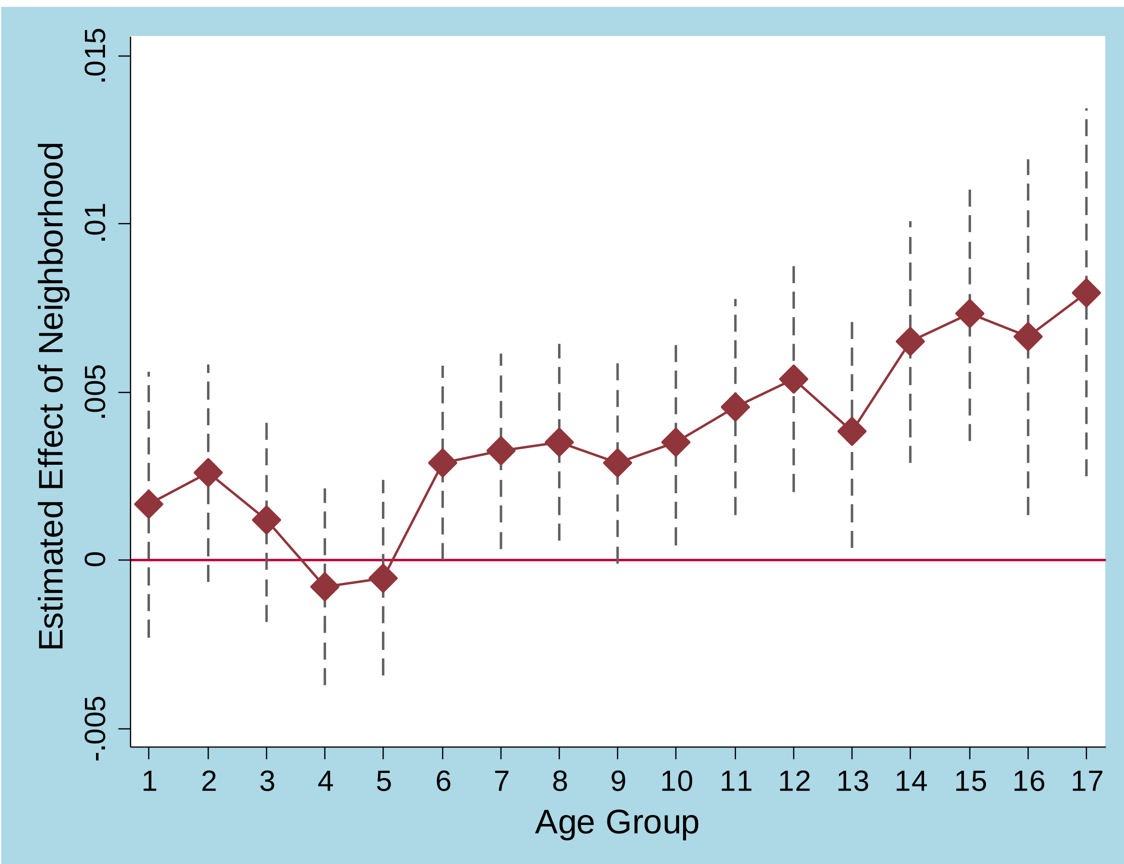


Figure 13C
Impact of BA Plus on Enrollment
(1 year of Exposure to 1 Std Higher)
More finely tuned measure

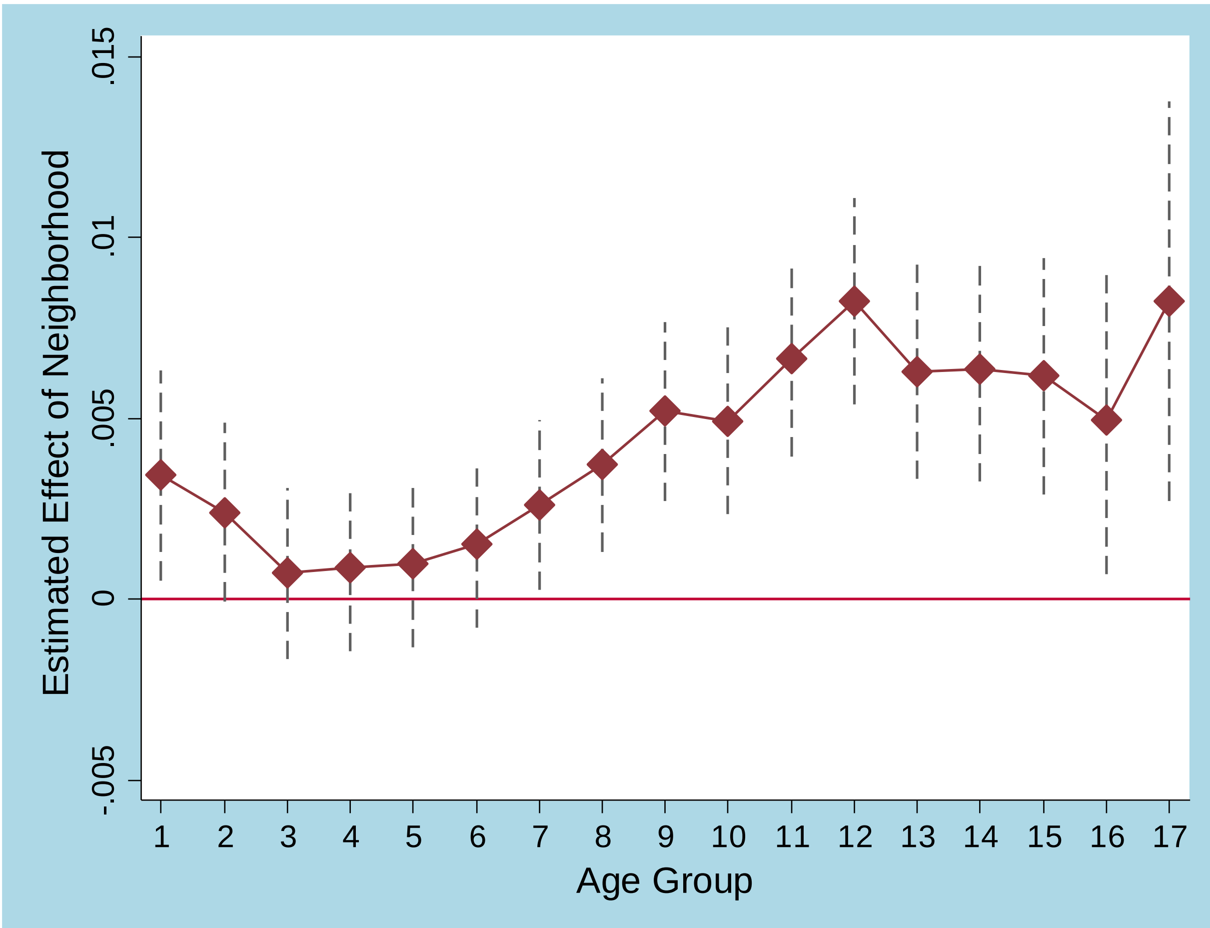


Figure 14

Impact of Chetty Hendren Causal Measure on College Going
(One Year's Exposure on Outcome)

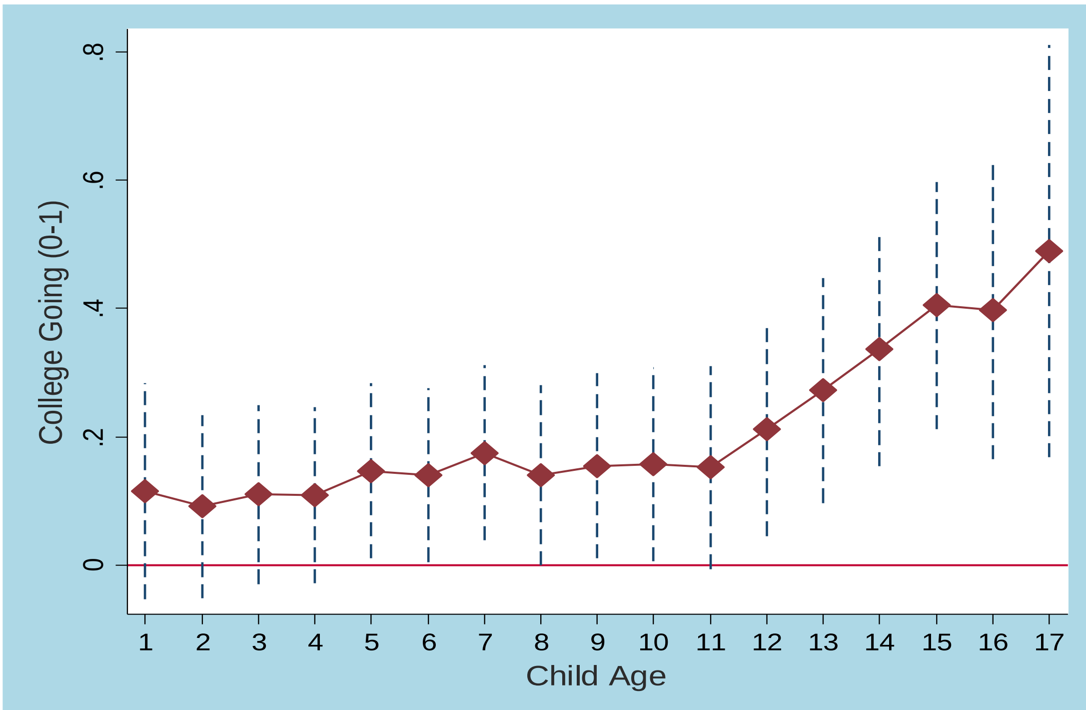


Figure 14B
Impact of Chetty Hendren Causal Measure on College Going
(One year of Exposure to 1 Std Higher)

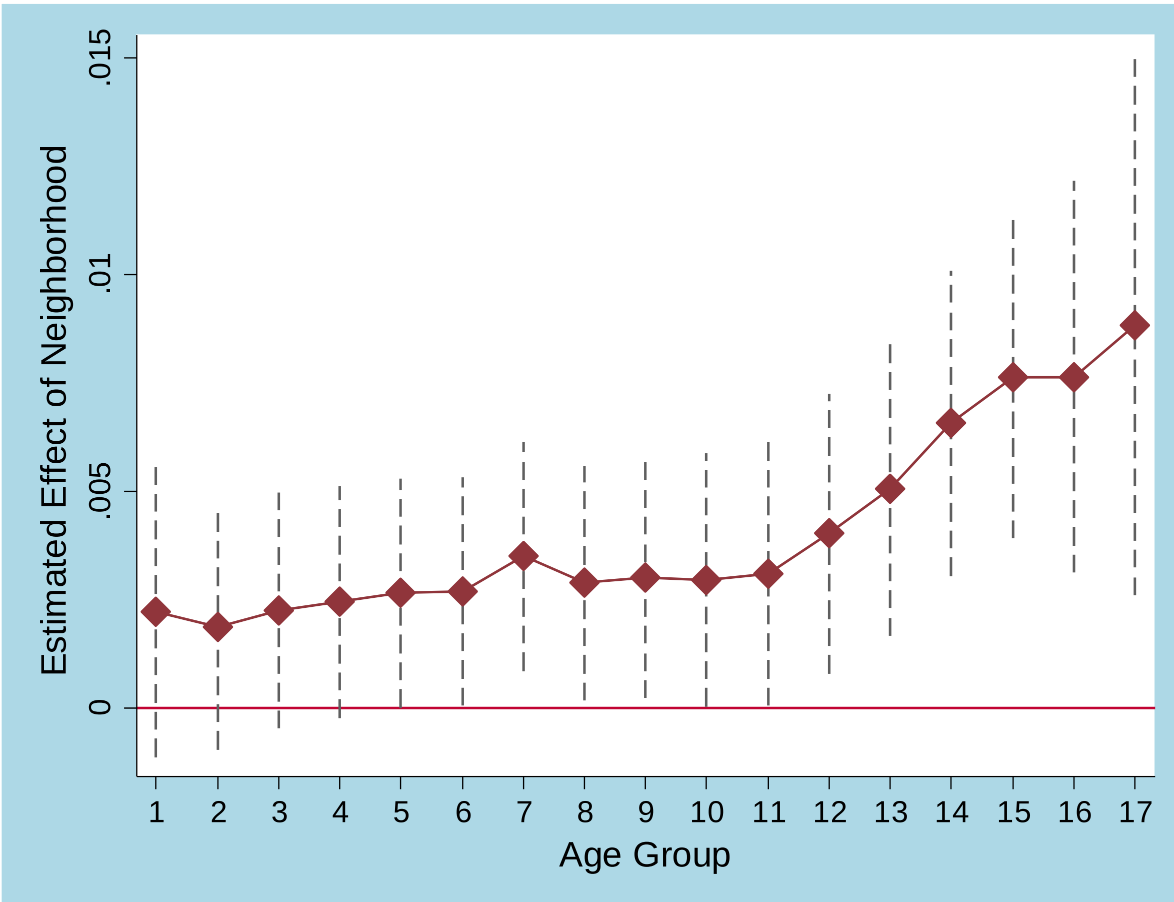


Figure 14C
Impact of Chetty Hendren Causal Measure on College Going
(Grouped by Ages One year of Exposure to 1 Std Higher)

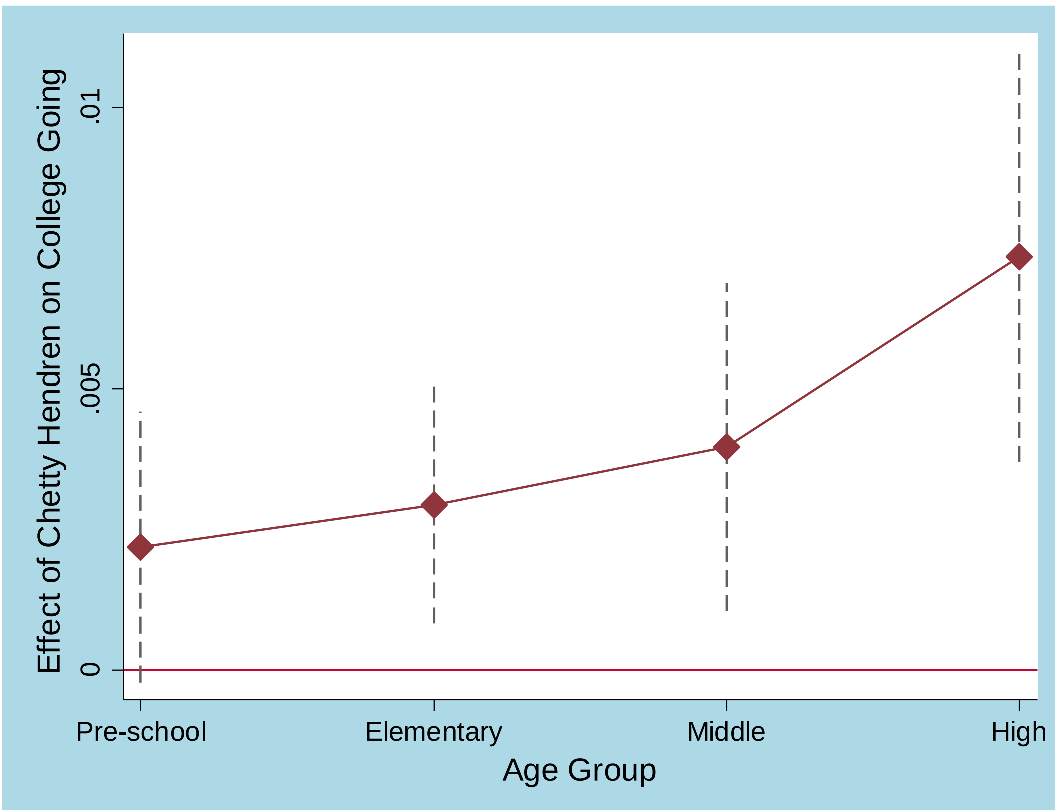
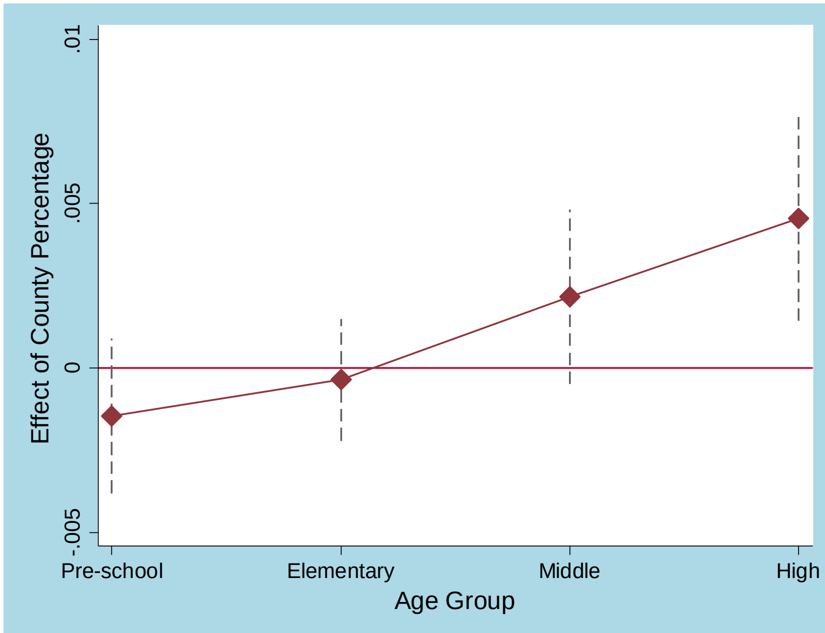


Figure 15
Effect of County Percentage Above 150% Poverty on College Going
(1 Year of Exposure to 1 Std Higher)



Effect of County Percentage > Poverty on College Going 4+ Yrs

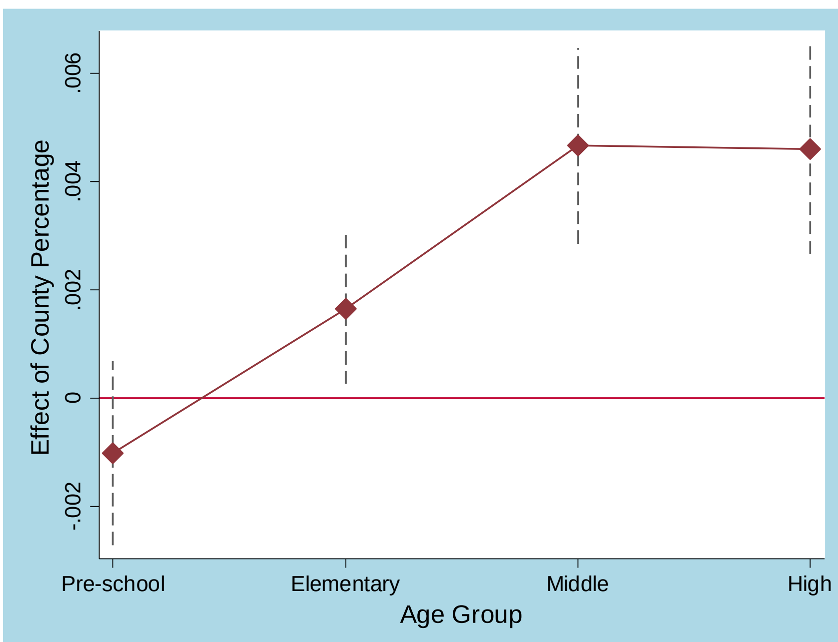


Figure 16
Effect of Math Test Scores (in County) on College Enrollment
(1 Year Exposure to 1 Std Higher)

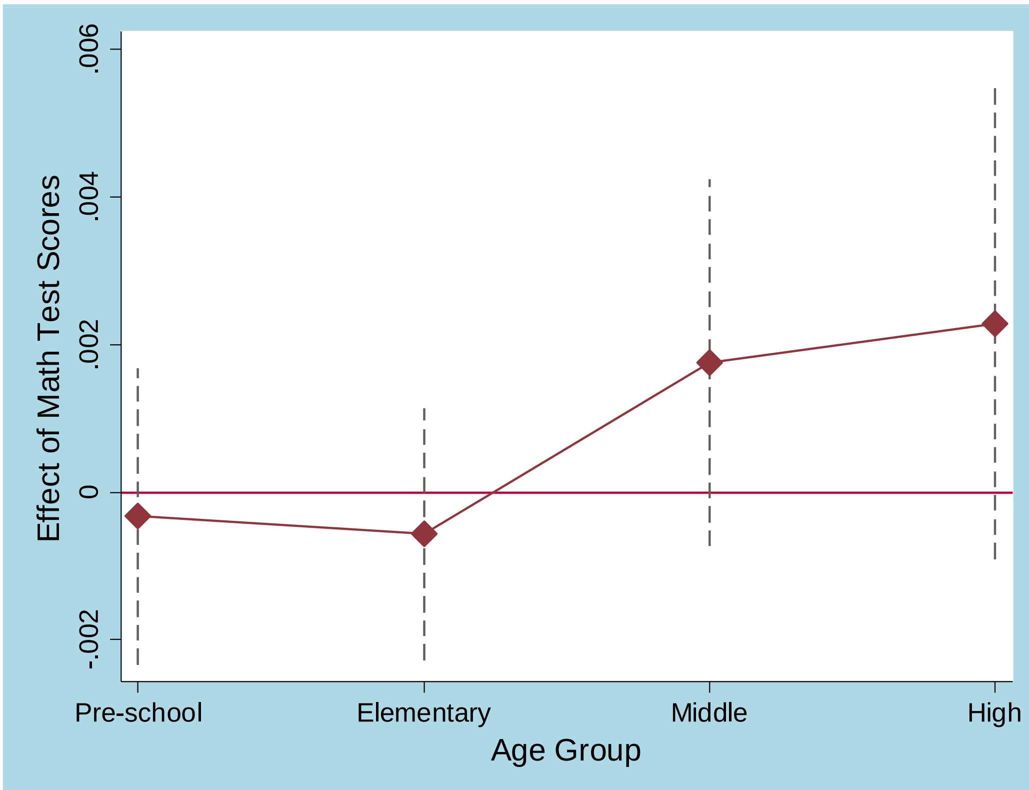
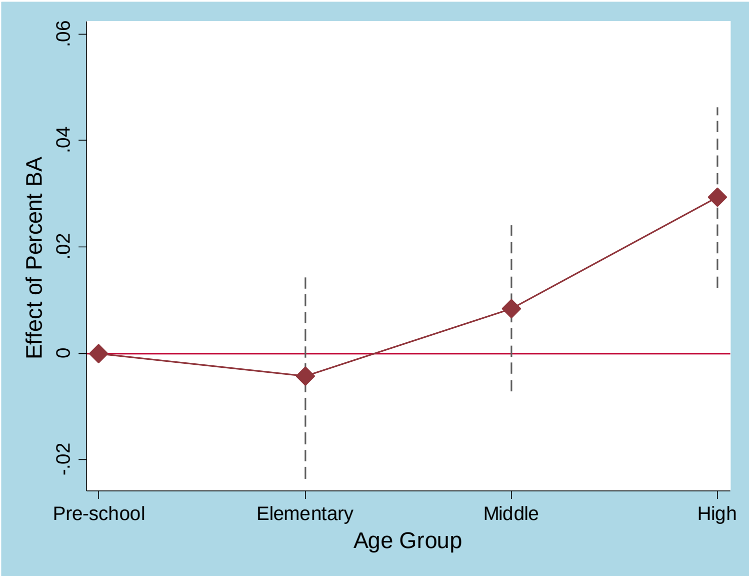


Figure 17
Impact of Percent BA on Log Wages at Age 30



Impact of Percent BA on Log Zip Code Income at Age 30
(1 Year Exposure to 1 Std Higher)

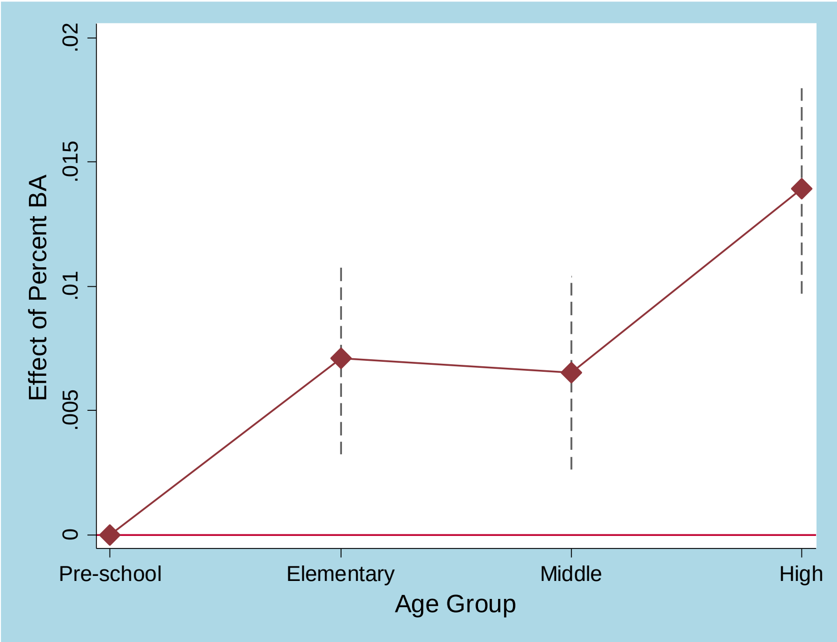


Figure 18

Impact of Chetty Hendren College Causal Measure on Log Wages Age 30

(1 Year Exposure to 1 Std Higher)

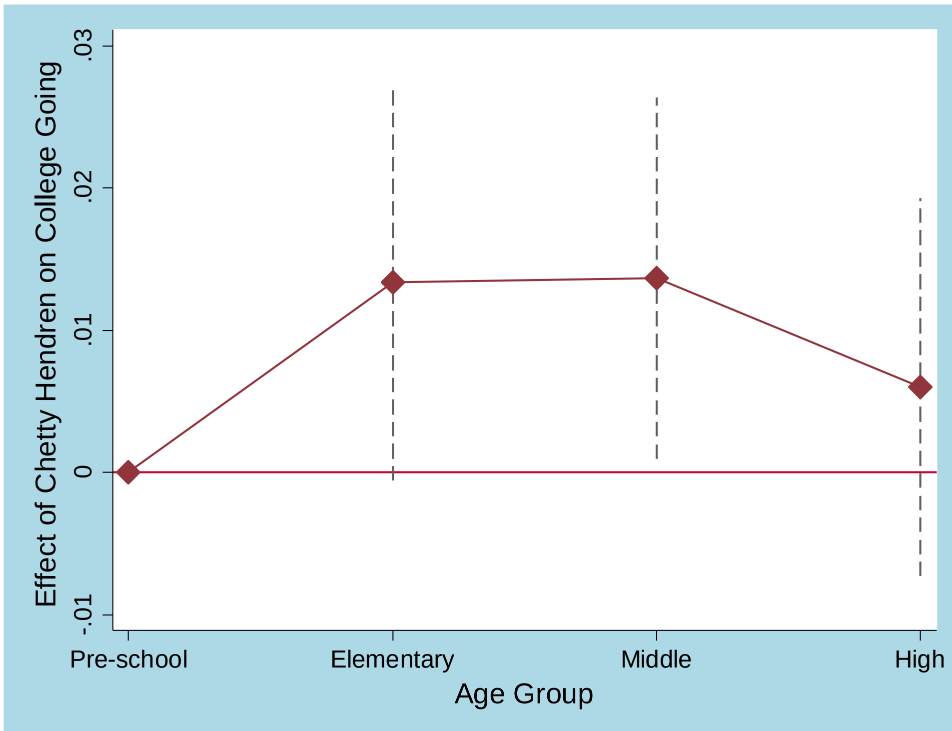
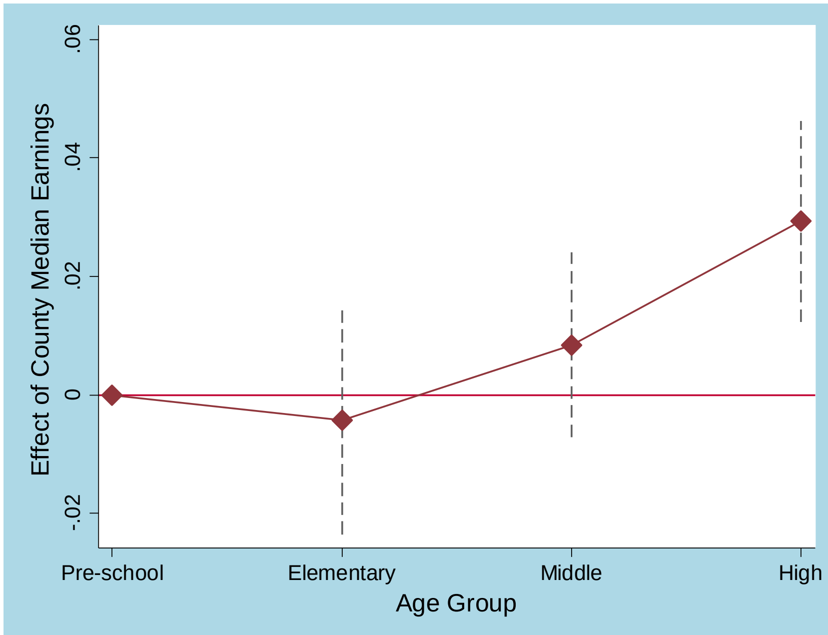


Figure 19
Impact of County Median Earnings on Log Wages at 30
(1 Year Exposure to 1 Std Higher)



Impact of County Median Earnings on Zip Code Income at 30

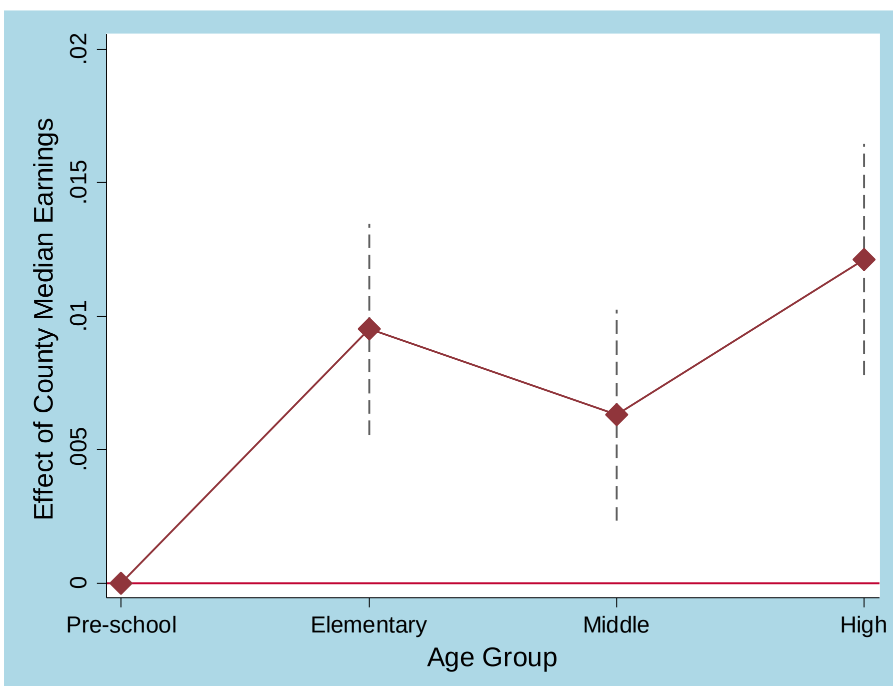


Figure 20

Chetty Hendren Income Causal Measure Impact on Percentile of Wages at Age 30

(Native Units)

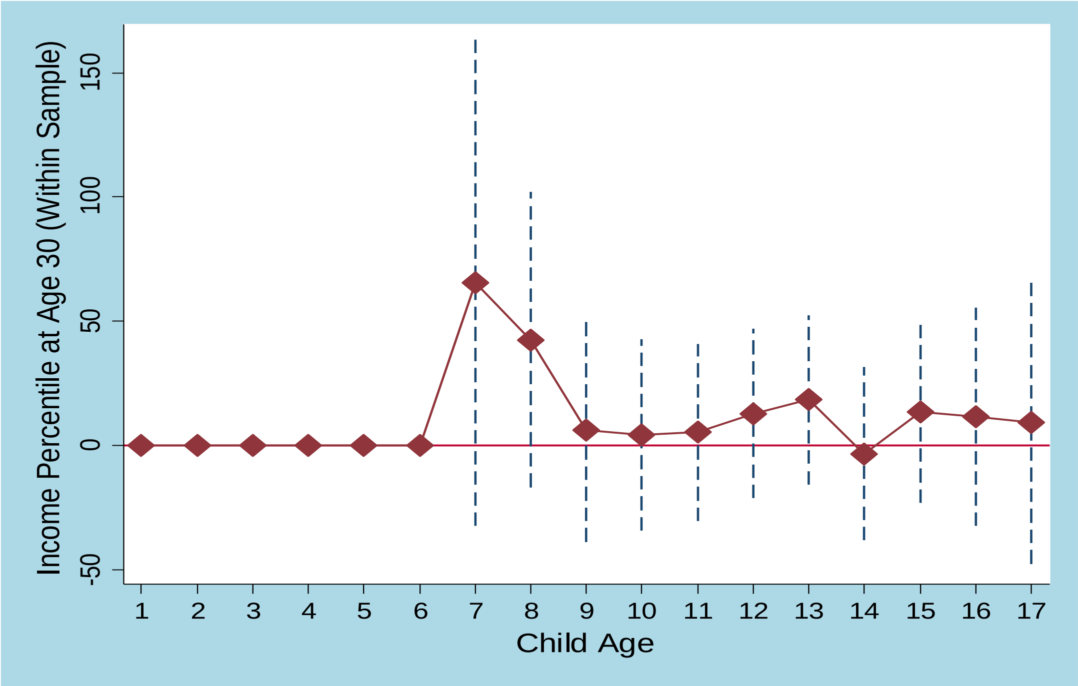
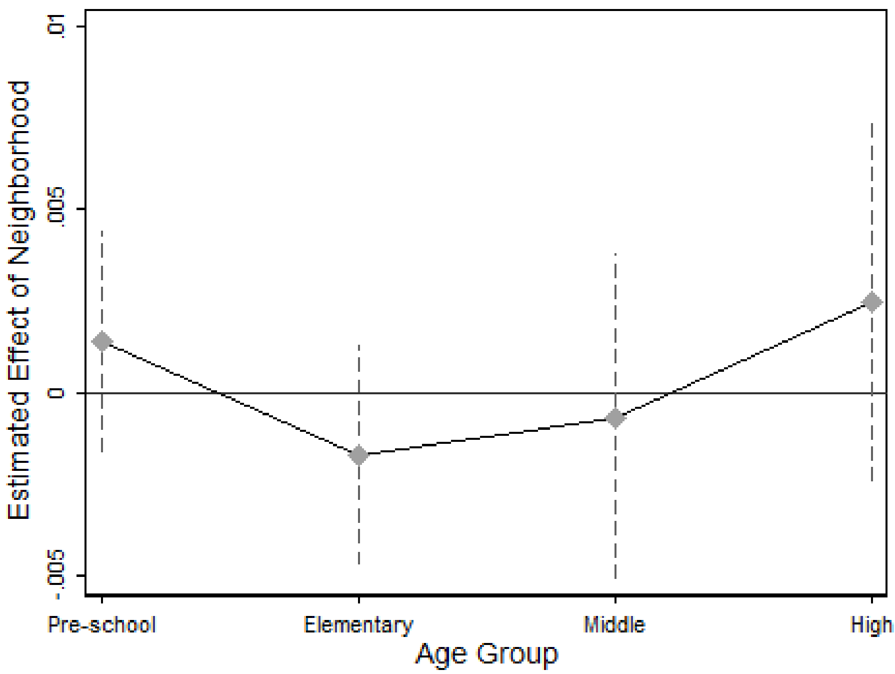


Figure 21

OCONUS on College



OCONUS on College 4+ Years

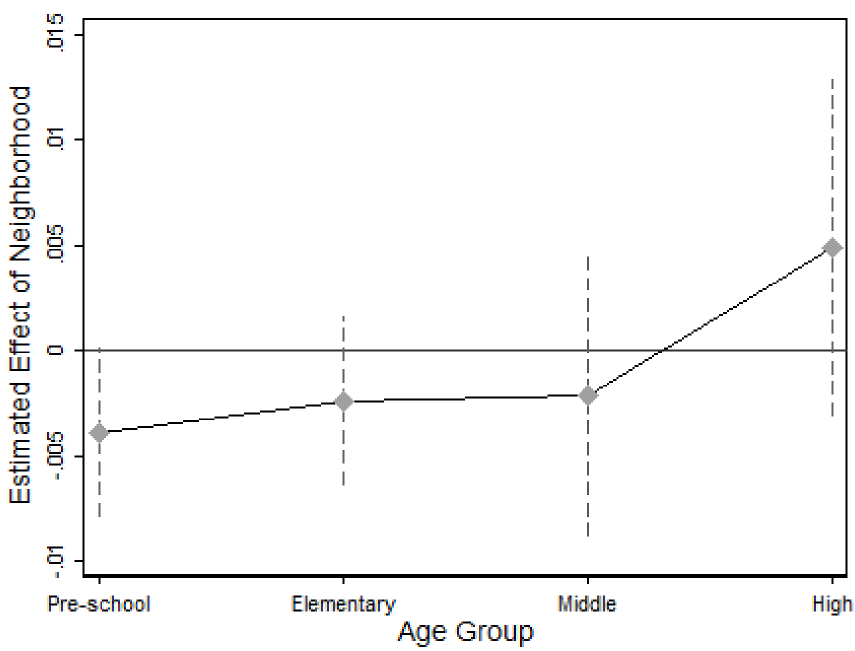
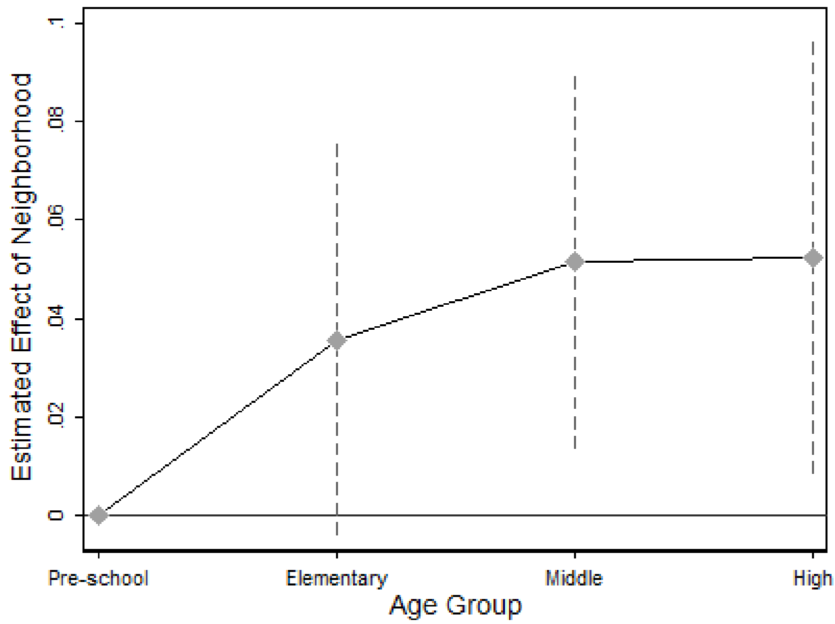


Figure 23

OCONUS on Wages



OCONUS on Log Wages at 30 (Single Ages)

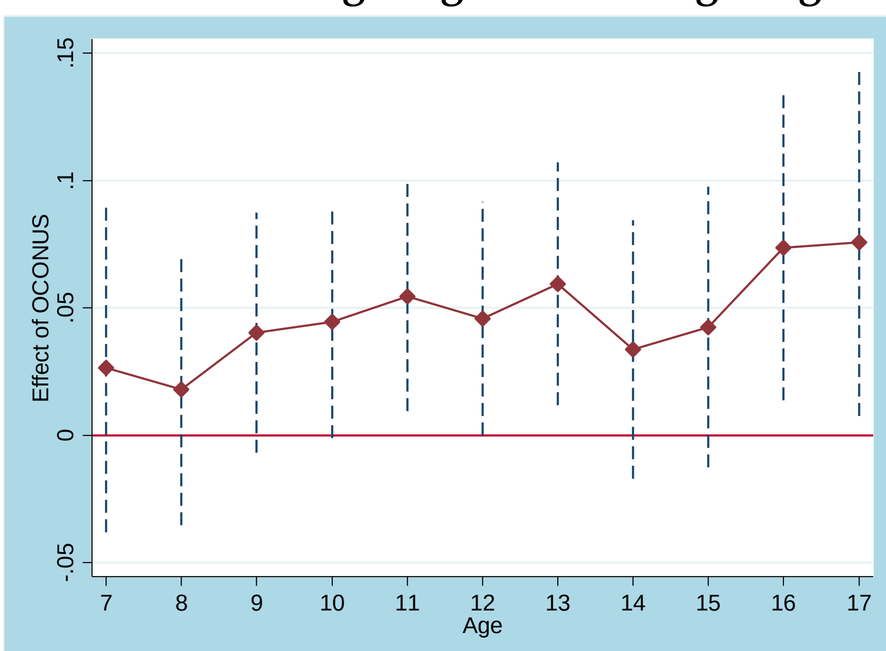


Figure 24

Impact of Assignment to Germany on Log Wages at 30

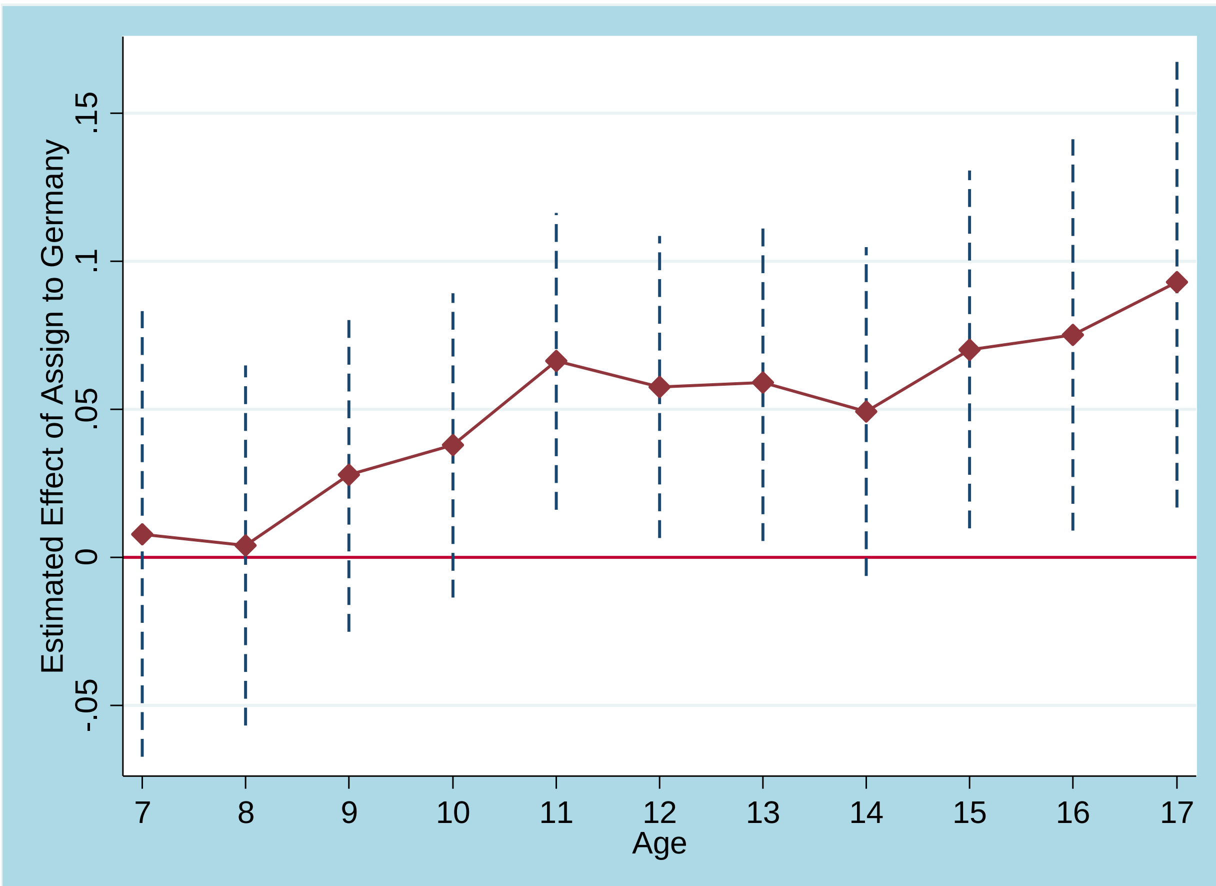


Figure 25

Impact of Assignment to Italy on Log Wages at 30

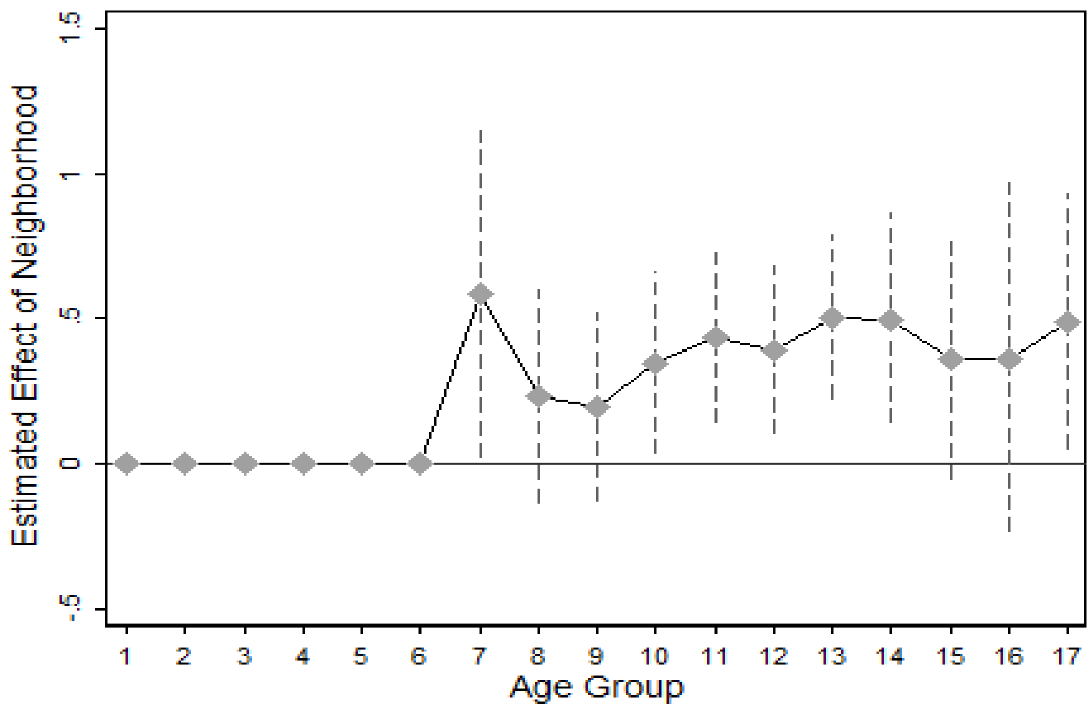
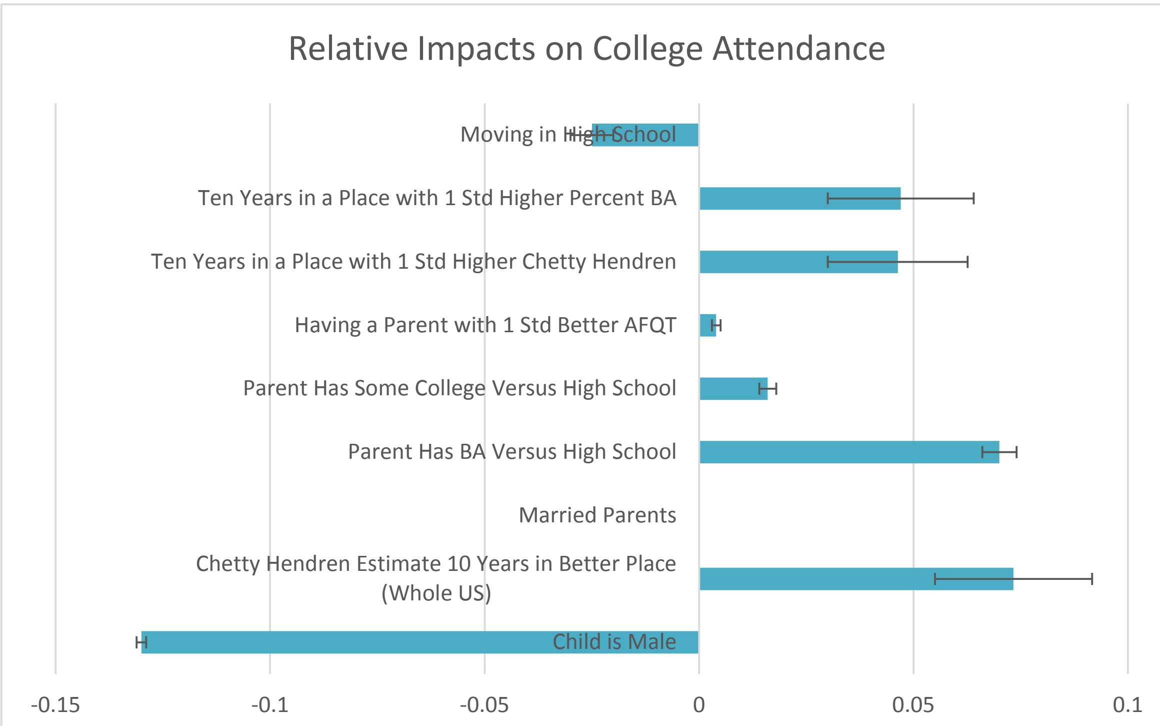


Figure 26

Relative Impacts on College Attendance



Appendix Table 1

Frequency Tab at Largest Bases Cont US

Army Location Name	Oconus?	Zip	Number Assignments
Ft Hood, TX	0	76,544	379,714
Ft Bragg, NC	0	28,305	339,754
Ft Campbell, KY	0	42,223	222,503
Jblm Lewis, WA	0	98,433	180,055
Ft Carson, CO	0	80,913	161,585
Ft Stewart, GA	0	31,313	144,379
Ft Benning, GA	0	31,905	134,624
Ft Bliss, TX	0	79,906	128,168
Ft Riley, KS	0	66,442	121,693
Schofield Brks, HI	0	96,857	118,761
Ft Drum, NY	0	13,601	112,547

Appendix Table 2

Frequency Tab at Largest Bases OCONUS

Army Location Name	Oconus?	Zip	Number Assignments
CP Casey (KS)	1	96,224	65,240
Yong San (KS)	1	96,205	45,504
CP Humphreys (KS)	1	96,271	36,804
Baumholder (DE)	1	9,034	31,631
Wiesbaden (DE)	1	9,117	29,322
Schweinfurt (DE)	1	9,033	29,082
Hanau (DE)	1	9,165	25,392
Kaiserslautern (DE)	1	9,229	23,296
Vilseck (DE)	1	9,112	22,841
Heidelberg (DE)	1	9,099	21,653
Mannheim (DE)	1	9,296	20,281
CP Stanley (KS)	1	96,258	19,888
Kitzingen (DE)	1	9,514	19,216

Appendix Table 3

Examples of Jobs: PMOS

Parents Pmos	Freq.	Percent	Cum.
11B Infantryman	90,795	9.58	9.58
88M Motor Transport Operator	39,867	4.21	13.78
92Y Unit Supply Specialist	29,697	3.13	16.92
91B	29,309	3.09	20.01
13B Cannon Crewmember	27,642	2.92	22.92
68W Health Care Specialist	27,194	2.87	25.79
92A Automated Logistical Specialist	26,217	2.77	28.56
92G Food Service Specialist	23,527	2.48	31.04
19K M1 Armor Crewman	22,661	2.39	33.43
31B Military Police	22,608	2.38	35.81
42A Human Resources Specialist	21,178	2.23	38.05
19D Cavalry Scout	21,022	2.22	40.26
92F Petroleum Supply Specialist	19,552	2.06	42.33
63B Light Wheel Vehicle Mechanic	14,991	1.58	45.7
25U Signal Support Systems Specialist	12,991	1.37	47.07
74D Chemical Operations Specialist	12,640	1.33	48.4
79R Recruiter NCO	12,540	1.32	49.73
13F Fire Support Specialist	12,162	1.28	51.01
11C Indirect Fire Infantryman	11,484	1.21	52.22
25B Information Tech Specialist	9,926	1.05	53.27
15T Medium Helicopter Repairer	6,722	0.71	56.52
25Q Comm Systems Maintenance	5,785	0.61	58.47

Appendix Table 4

Military Kids Living on Base/Off Base

Base Name	Live on Base	Live Off Base	Total	DoDea Enrollment
Fort Belvoir, VA	3,625	12,473	16,098	0
Fort Bragg, NC	1,050	30,286	31,336	0
Fort Carson, CO	4,112	12,137	16,249	0
Fort Hood, TX	6,039	16,190	22,229	0
Fort Sam Houston, TX	2,300	9,980	12,280	0
Ft Monroe, VA	1,819	13,104	14,923	0
Ft Story, VA	3,392	13,357	16,749	0
Jblm Lewis, WA	5,037	8,325	13,362	0
Pentagon, VA	2,058	9,630	11,688	0
Schofield Brks, HI	9,614	4,335	13,949	0

Appendix Table 5

School in County/Out of County

Base Name	School Not in County	School in County	Total
Fort Belvoir, VA	5,273	10,825	16,098
Fort Bragg, NC	11,588	19,748	31,336
Fort Carson, CO	0	16,249	16,249
Fort Hood, TX	5,040	17,189	22,229
Fort Sam Houston, TX	2,011	10,269	12,280
Ft Monroe, VA	8,460	6,463	14,923
Ft Story, VA	3,634	13,115	16,749
Ft Monroe, VA	8,460	6,463	14,923
Ft Story, VA	3,634	13,115	16,749
Jblm Lewis, WA	5,432	7,930	13,362
Pentagon, VA	863	10,825	11,688
Schofield Brks, HI	0	13,949	13,949

Appendix Table 6

Difference in Ages Between 0-7 and 7-17

Variable	Mean ages 0-7	Mean ages 7-17	T Test for the Difference
Child Age	10.91	2.30	1200.00
Male	0.85	0.92	-71.50
Black	0.31	0.28	18.81
Hispanic	0.12	0.11	3.39
Other race	0.06	0.06	1.43
Parents AFQSC	55.62	55.93	-4.94
High School Dropout	0.00	0.01	-5.78
High School Graduate	0.66	0.71	-37.79
Some College	0.26	0.22	26.37
College	0.07	0.05	25.65
Graduate	0.01	0.01	10.49
Parents Ever Married	0.43	0.49	-33.81
Parents Number of Dep.	3.93	3.55	66.02
Location_S~R	1999.40	1999.91	-22.63
Percent_Ba~Y	0.15	0.15	-14.32
Raj_Colleg~T	-0.04	-0.04	0.80

Appendix Table 7

Create more Sophisticated Measures of Demographics Around Base

	(1)	(2)	(3)	(4)
	Percent BA: Weight Zip Codes by Army Dependent Presence	Chetty Hendren Measure: Weight Counties by Army Dependent Presence	Nat'l Math Percentile: Weight LEAs by Army Dependent Presence	Nat'l Reading Percentile: Weight LEAs by Army Dependent Presence
Percent BA Basic	0.770***			
County Level	(0.0797)			
Chetty Hendren Basic		0.909***		
County Level		(0.0353)		
National Math Percentile			0.756***	
Basic County Level			(0.0595)	
National Reading Percentile				0.655***
				(0.0638)
Observations	42	41	40	40
R-squared	0.7	0.945	0.81	0.735

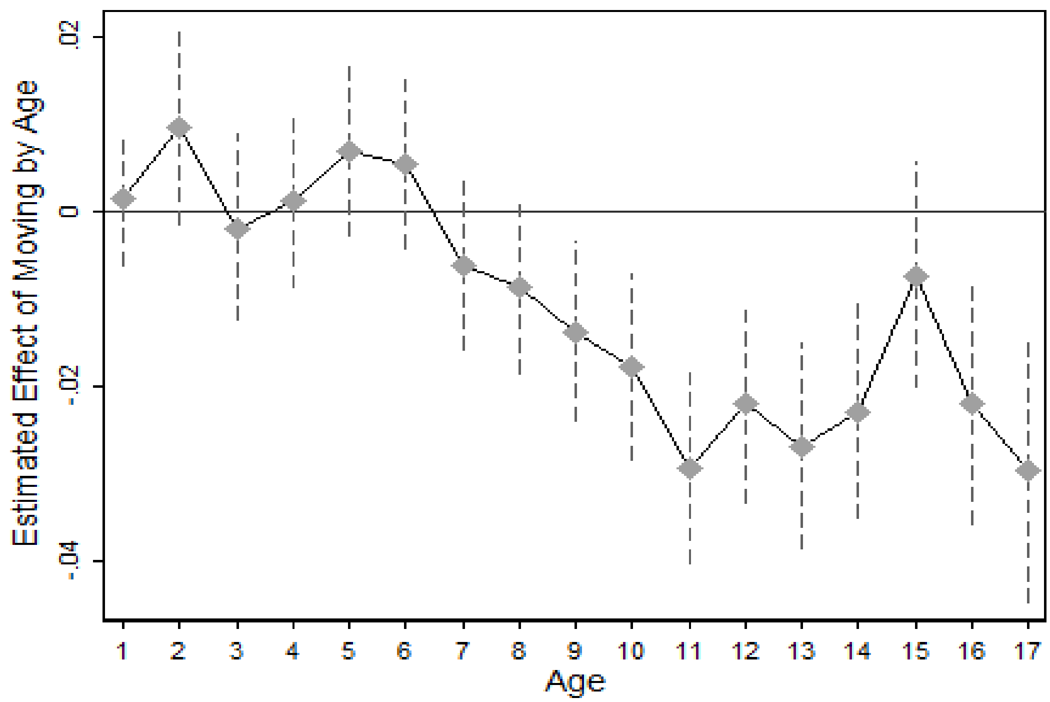
Appendix Table 8

Impact of Chetty Hendren College Going Measure on College Going in Our Sample (Native Units)

	(1)	-2
	College Attendance	College Attendance
	college	For Four Years
Chetty Hendren College Going Measure	0.455***	0.152
	(0.152)	(0.152)
Pre-School Age	0.001	0.001
	(0.003)	(0.002)
Elementary Age	0.007***	0.009***
	(0.002)	(0.002)
Middle School Age	0.003**	0.003***
	(0.002)	(0.001)
o.highschool	-	-
Parent is Black	0.039***	0.017***
	(0.002)	(0.001)
Child is Male	-0.145***	-0.072***
	(0.002)	(0.001)
Parent AFQT (Z score)	0.010***	0.006***
	(0.001)	(0.001)
par_HSD	0.031**	0.025***
	(0.016)	(0.009)
Parent is HS Grad	0.044***	0.017***
	(0.004)	(0.002)
Parent Associates Degree	0.094***	0.050***
	(0.005)	(0.003)
Parent Some College	0.075***	0.035***
	(0.005)	(0.003)
Parent College	0.130***	0.076***
	(0.006)	(0.004)
Parent Grad School	0.137***	0.089***
	(0.009)	(0.008)
Observations	1,556,220	1,556,220
R-squared	0.216	0.182

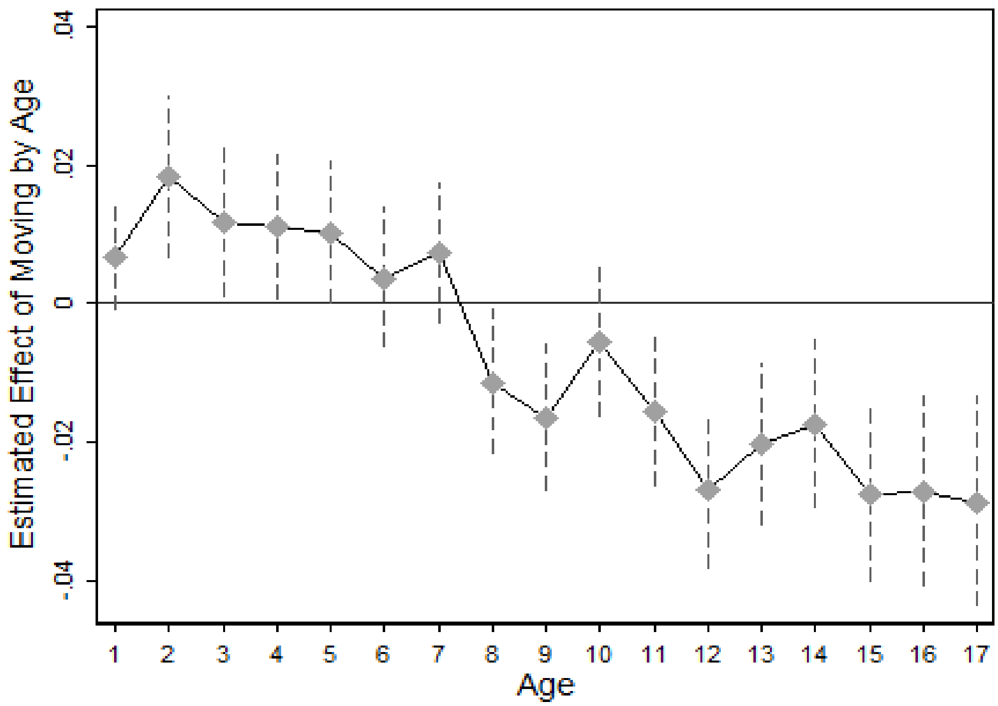
Appendix Figure 1

Impact of Moving on College Enrollment by Age (Female)

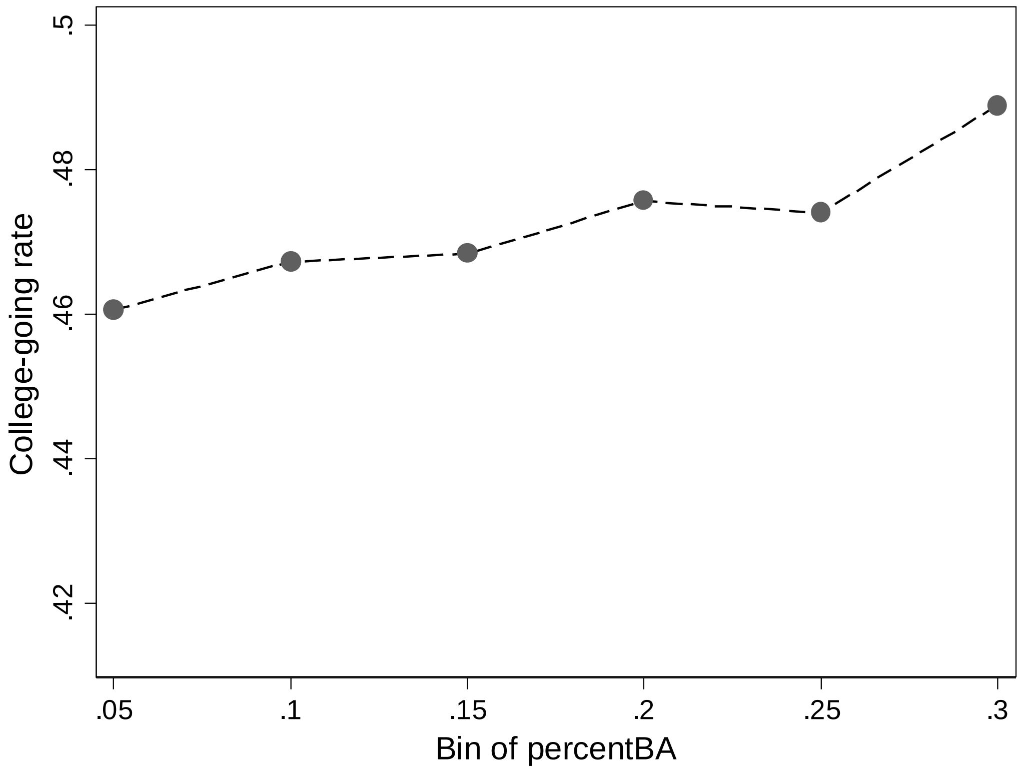


Appendix Figure 2

Impact of Moving on College Enrollment by Age (Male)

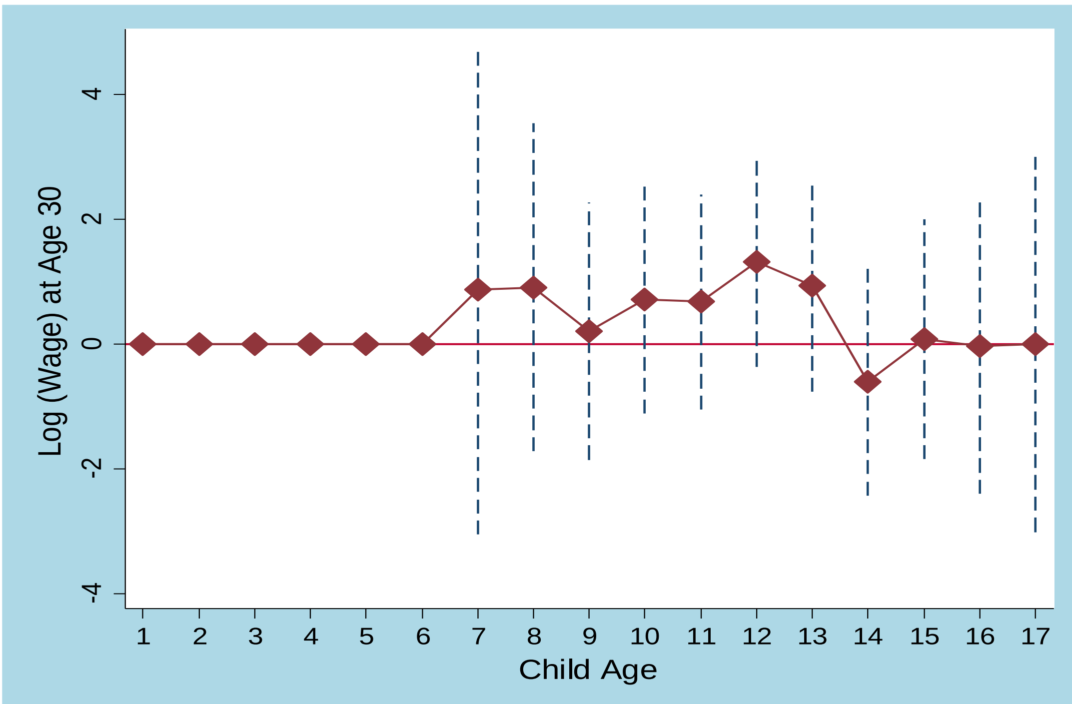


Appendix Figure 4
Binned Scatter Plot of College Enrollment on Percent BA in High School



Appendix Figure 5

Chetty Hendren Income Causal Impact on Log of Wages at 30



Appendix Figure 6

Impact of Chetty Hendren College Causal Measure on Zip Code Income at Age 30