UNIVERSITY OF CALIFORNIA,
IRVINE

Belief Revision and Machine Discovery

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Nanneh Chehras

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2017

DEDICATION

To my family for their love and support.

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I would like to thank my family for their unconditional love and support. Thank you to my parents, Anouche and Haydouk Chehras, for instilling a sense of determination that has guided me throughout my life. Without their unwavering faith in my abilities, I would not be here today. I would like to thank my sister, Naira Chehras, for encouraging me and giving me a sense of purpose. Thank you for being my pillow and punching bag, and for always having my back.

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ABSTRACT OF THE DISSERTATION

Essays in Education and Labor Economics

By

Nanneh Chehras

Doctor of Philosophy in Economics

University of California, Irvine, 2017

Professor David Neumark, Chair

This dissertation studies educational attainment and immigrant assimilation using applied econometric methods.

The first chapter estimates the effect of high school counselors on dropout rates using difference-in-differences methods and a large-scale policy change. I exploit within school student-to-counselor ratio variation in California's public high schools between 2003 and 2015. The analysis finds that decreases in the student-to-counselor ratio are associated with decreases in dropout rates. For example, a 100-student decrease in the student-to-counselor ratio would decrease the overall dropout rate by 1.7 percentage points. I further show that under conservative assumptions, the costs associated with decreases in the student-to-counselor ratio are offset by the social benefits.

The second chapter provides a novel measure of the science, technology, engineering, and mathematics gender gap. Using data science methods, I construct a dataset of high school and middle school science fair projects and use project choices of over 17,000 students to measure gender gaps. I find large gender gaps favoring males in technology, engineering, and mathematics fields that increase across age. For example, the gender gap among middle

school math participants is 34 percentage points, increasing to 40 percentage points in high school. Similarly, the gender gap among engineering participants increases from a substantial 26 percentage points in middle school to 29 percentage points in high school.

The third chapter explores the role of child-sex composition preferences on fertility assimilation outcomes for Chinese, Indian, and South Korean women in the United States. Using Census and American Community Survey data, I first determine the sex-composition preferences among immigrant and native women. I then introduce these preferences in the assimilation framework, employing ordinary least squares regressions to determine the fertility differential between immigrants and natives. I show that once second-generation immigrants adopt the native preference for mixed-sex children, their childbearing behavior becomes similar to natives and fertility assimilation occurs.

CHAPTER 1

Can Counselors Help Solve the Dropout Crisis? Evidence from California's Public High Schools

1.1 INTRODUCTION

The national dropout rate garners concern among researchers and policymakers.[1] [2] Compared to graduates, high school dropouts experience higher rates of unemployment, criminal activity, and public assistance dependence, while exhibiting lower earnings and poorer health outcomes. Studies estimate that the social cost of an average dropout exceeds $250,000 (Rouse, 2005; Belfield and Levin, 2007; Sum et. al, 2009). Policies designed to improve educational attainment, including early childhood intervention, classroom size reduction, and large-scale school reform, receive mixed results. Currently, there is no consensus around the most effective policy to improve educational outcomes (Murnane, 2013). However, notably absent from the research is the role of high school counselors, individuals who are tasked with both identifying and preventing dropouts.

The American School Counselor Association (ASCA) recommends one counselor for every 250 enrolled students. Satisfying this recommendation requires significant increases in current counseling departments. For example, if California's public school system employed enough additional counselors to meet ASCA's student-to-counselor ratio, then there would be 70 percent increase in the number of counselors per school. Proponents of

[1] Throughout the paper, I adopt the convention to refer to the share of enrolled students who drop out as the dropout rate.

[2] During the first seventy years of the twentieth century, the high school graduation rate increased from six to 80 percent (Goldin and Katz, 2008; Heckman and Fontaine, 2010). This upward trend increased the proportion of the labor force with high school degrees and was an important factor that fueled economic growth (Goldin and Katz, 2008; Hanushek and Woessman, 2008).

such increases highlight that high school counselors address personal problems and development, schedule classes, offer information about postsecondary options, and broadly promote academic, personal, and career success (Ingels and Dalton, 2013). Nevertheless, with limited fiscal resources and no causal evidence to support counseling benefits, the argument to hire more school counselors is often ignored. Thus, with potentially large social implications, the evaluation of high school counselor effects is of first-order importance.

In this paper, I present improved evidence about the relationship between high school student-to-counselor ratios and student outcomes using data on all California public high schools. Specifically, I introduce difference-in-differences methods to exploit within school variation while controlling for a variety of student and staffing variables. Furthermore, data on dropout rates by grade allow for the estimation of potentially differential counselor effects throughout high school.

Beyond establishing an improved measure of the relationship between high school student-to-counselor ratios and student outcomes, studying California's public schools offers three further advantages. First, although California is the largest state in terms of enrollment and accounts for 12 percent of all students in the country, it produces over 20 percent of the nation's dropouts (National Education Association, 2014).[3] Second, California's four-year high schools employ over 3,800 counselors and have some of the highest student-to-counselor ratios in the country. Thus, counseling increases in California specifically may lead to above average improvements in national statistics. Finally, there is

[3] The second largest state in terms of number of enrolled students is Texas, which accounts for seven percent of the total dropouts in the country (Stillwell and Sable, 2013).

adequate variation in student-to-counselor ratios. Specifically, the 2008 Middle and High School Counseling Program, a $200 million grant to hire new counselors, caused a one-time 20 percent increase in the number of high school counselors. Immediately following this increase, school counseling levels declined and returned to their initial levels with substantial variation across schools in the exact timing of counseling department changes.

The analysis shows that there is a positive relationship between student-to-counselor ratios and the overall dropout rate, indicating that increased student caseloads are associated with higher dropout rates. This positive relationship is statistically significant in the post-grant period, where there is increased counselor variation. For example, a 100 student decrease per counselor (resulting in 370 students per counselor) would decrease the overall dropout rate by 1.7 percentage points. To meet ASCA's recommendations, if there is a decrease of 220 students per counselor to meet ASCA's recommendations, then the overall dropout rate would be effectively driven to zero. A more conservative and realistic decrease to a ratio of 400 students per counselor would lead to 14 less dropouts per year, compared to the average of 34 dropouts per year.[4]

To add context to the dropout rate results, I show that alternative programs that improve high school graduation outcomes produce a wide range of effect sizes from one to 25 percent. However, these alternative programs are often costlier. I compare the cost-effectiveness of counseling programs to the other dropout reduction efforts and conduct a cost-benefit analysis. To achieve the previously mentioned 70 student decline per counselor, each school would need to invest about $10,000 in counseling, assuming no

[4] These results are robust to controlling for potential omitted variables, including the school teachers, psychologists, social workers, nurses, librarians, and the administration's experience.

changes in the number of students. Studies that calculate the social cost of average dropouts produce statistics that exceed $200,000. Although it is unclear if reductions in student-to-counselor ratios affect the average dropout, the $10,000 cost is surely offset by the social benefits from the 14 student decline in dropouts.

1.2 COUNSELING SERVICES AND POLICIES IN CALIFORNIA

To motivate potential counselor effects, I first explain counselor responsibilities using formal job descriptions and data from counselor surveys. I then provide a literature review of high school counselor research. Finally, I describe changes in California's counseling policies, including the Middle and High School Counseling Program, which generates the variation used in the analysis below.

1.2.1 Counselor Responsibilities

The American School Counselor Association (ASCA) outlines general and grade-specific counselor responsibilities. Counselors assist in individual student academic planning and personal development. In addition to students, counselors also collaborate with parents, teachers, and administrators. Grade-specific tasks include assisting in the middle to high school transition among 9th graders and promoting performance on the California High School Exit Exam (CAHSEE) among 10th graders. Counselors provide 11th grade students information about postsecondary options and provide 12th grade students recommendation letters and assistance with postsecondary applications. Importantly, counselors must also identify at-risk students in grades 10 through 12 based on CAHSEE performance, coursework, and grades. Guidance counselors are required to schedule individual meetings with these students and their parents or legal guardians. About twothirds of students and half of parents talk with a school counselor by the spring of the student's 11th grade year (Ingles and Dalton, 2013).

The High School Longitudinal Study of 2009 asks counselors to estimate the percentage of time their school's counseling department spent on various activities during the previous school year. Although most schools offer information on college admission tests, colleges, and financial aid, about half of counselors report departments spent less than 20 percent of time on these activities. On the other hand, about half of counselors report that their counseling departments spent more than 20 percent of their time on course choice and scheduling, while about 30 percent of counselors spent more than 20 percent of their time on academic development. These counselor activities collectively contribute to the goal of high school graduation by using various benchmarks to identify students who are not on track to graduate.

1.2.2 High School Counselor Literature Review

Studies analyzing high school counselor effects rely on cross-school variation. Carey, Harrington, Martin and Stevenson (2012) study public high schools in Utah and find that increasing the number of counselors leads to improvements in graduation rates, discipline rates, attendances rates, and test scores. Carey, Harrington, Martin, and Hoffman (2012) find similar results on attendance, discipline, and suspension rates in rural high schools in Nebraska. Similar patterns emerge in Connecticut (Lapan, Whitman, and Aleman (2012) and Lapan, Gysbers, Stanley, and Pierce (2012)).

These studies are restricted to a single year of data and use cross-school variation in counseling with minimal controls for school differences, often just school demographics or percent Free and Reduced Price Meals (FRPM). Hurwitz and Howell (2014) attempt to overcome these shortcomings by adopting a regression discontinuity approach to compare high schools within a state that fall on either side of a student-to-counselor threshold in terms of enrollment. They find that an additional counselor increases four-year college-going rates by a substantive 24 percent. However, their paper does not test for the validity of the regression discontinuity design,[5] and the authors acknowledge that "beyond stating that additional counselors do exert a causal impact on the 4-year college-going rates, we feel less comfortable accepting these fairly large point estimates as gospel" (pages 322-323).

Generally, high school counseling departments exhibit minimal variation, which prevents the use of panel data methods to account for unobserved time-invariant factors. In this paper, I utilize the variation primarily attributed to the largest counseling grant in the U.S. Thus, I am able to use school fixed effects and detailed staffing variables to advance shortcomings in the literature.

1.2.3 California Counselor Policies

To be a school counselor in California, individuals must complete a graduate program from a California Commission on Teacher Credentialing (CCTC) accredited institution that grants a credential in Pupil Personnel Services (PPS) with a Specialization in School Counseling. Individuals must also pass the California Basic Educational Skills Test, complete a practicum with school-aged children with a minimum of 100 hours, and obtain

[5] For example, they do not test if the average value of the covariates are discontinuous at the threshold, if the density of the assignment variable is continuous at the threshold, and if there are jumps at non-threshold points. They also do not explain the choice of bandwidth, which is rather large at 125 students, and do not address why the 2SLS estimates are four times the magnitude of the OLS estimates.

a formal recommendation from a California college or university with a CCTC-accredited PPS program.[6] [7]

California does not employ any student-to-counselor ratio requirements. The most notable change in the counseling field in the last several decades is the Middle and High School Supplemental School Counseling (MHSC) program. This grant provided approximately $78 per prior year enrollment to hire additional school counselors in grades seven through 12. Funding was specific to new counselors, as opposed to existing credentialed staff. Districts that served at least 100 students in grades seven through 12 were eligible to apply. Ultimately, 97 percent of districts in the state accepted funding.[8] Initially a recurring source of funding, after one year of disbursement, the requirement to spend the funds on counselors was removed. Local education agencies can use all of their program funds to provide services for the MHSC program or for other educational purposes and/or other categorical programs.[9] As a result, counseling services increased in 2008-2009, followed by a declining trend in aggregate counseling levels.

1.3 MEASURING GRADUAITON AND DROPOUT RATES

Measuring high school graduation and dropout rates is complicated by the sensitivity to data source and methodological choices, including how the General Education

[6] Credentials must be renewed every five years. In California, there are no additional requirements through the CCTC, other than application and fee. Professional growth requirements are the responsibility of the local employing agency.
[7] California Education Code, Section 44266 and Title 5, California Code of Regulations, Sections 80049- 80049.1 and 80632-80632.5
[8] Funding requirements indicated that school counselors must review each student's academic record, explain his or her education options (college preparatory program, vocational programs, etc.), and explain remaining coursework and other academic requirements. The program also required that counselors identify and meet with at-risk students and their parents or legal guardians.
[9] SBX3 4, Section 15, California Education Code Section 42605, enacted in February 2009.

Development (GED) credential is categorized. These student outcome measures come from three sources of data: household surveys, longitudinal data sets, and the Common Core of Data (CCD).[10] I focus the discussion on longitudinal data and the CCD, the sources that are available at the school-level.[11]

Longitudinal studies sponsored by the National Center for Education Statistics (NCES) and the U.S. Department of Labor follow a nationally representative sample of students over time. One issue with this data source is that nonrandom sample attrition implies that graduation rates are overestimated if students who drop out of school do not respond to follow-up surveys and are thus dropped from the analysis.[12] Further, surveying students starting in grade 10 poses an additional risk of overestimating graduation rates as it does not account for students who dropped out prior to grade 10.

The CCD represents an annual collection of data from local education agencies. Calculating the four-year graduation rate as the number of graduates in year t relative to the number of enrolled students at the beginning of year t-3 is complicated by the various

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[10] The Current Population Survey (CPS), the decennial Census of the Population, and the American Community Survey (ACS) report a "status completion rate" defined as "the percentage of individuals in a given age range who are not in high school and who have not earned a high school diploma or equivalency credential, irrespective of when or where the credential was earned" (Chapman et al., 2011).

[11] For a more thorough discussion, see Murnane (2013) and Mishel and Roy (2006).

[12] Most NCES sponsored longitudinal surveys, including the High School and Beyond and the Education Longitudinal Study of 2002, first sample adolescents when they are in grade 10. Using data from the National Education Longitudinal Study of 1988, which follows a large sample of students who are 8th graders in 1988, Altonji and Mansfield (2011) report that one-third of the survey participants who dropped out of high school did so before the first follow-up survey in grade 10.

paths students take through high school. Although some proposed improvements are less biased than others, none produce accurate estimates (Mishel and Roy, 2006).[13]

The limitations above highlight the importance of state administrative databases that track individual students. In 2008, the U.S. Department of Education issued regulations requiring that all states use longitudinal student data to calculate four-year cohort outcomes.[14] [15] Although an improvement in reporting standards, states are not required to report when a student drops out, limiting the ability to study within school variation in dropout timing.

The data used in this paper come from the California Department of Education. Annual dropout rates by grade are equivalent to the dropout rates used by the National Center for Education Statistics. Rates are calculated by dividing the total number of dropouts during the school-year by total enrollment at the beginning of the school-year. Schools are required to follow thorough and transparent student exit classification rules (Table 1 provides the full list). For example, dropouts do not include students who transferred to another public or private school in the U.S. Conversely, dropouts do include students initially reported as transfers, but not found enrolled in another school. The reliance on school enrollment data, ability to study grades within schools, and the thorough classification system provide advantages compared to alternative data sources.

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[13] For example, one solution is to use the "Average Freshman Graduation Rate" which divides the number of graduates with regular diplomas in year t by the average number of students enrolled in grades 8, 9, and 10 in years t-3, t-4, and t-5.

[14] Under the No Child Left Behind legislation, states that do not comply with the reporting requirements could lose federal funding of compensatory education (Title 1) programs.

[15] These regulations specify that states must drop students from a cohort if there is documentation that they enrolled in a private high school, moved to a different state, emigrated, or died. States are also required to count entering students, even if they enter in their final year, in the appropriate cohort when calculating the four-year graduation rate.

Changes in counseling departments could also affect transfer rates to alternative schools or programs. Due to data limitations, I cannot consider transfer rates as an alternative outcome variable. I do not claim that this paper's findings fully capture counselor effects. However, this paper does shed light on counselor impacts for two well-measured outcome variables: dropout and graduation rates.

1.4 METHODOLOGY

To estimate the causal effect of high school student-to-counselor ratios on student outcomes, counseling departments would ideally increase in size due to random assignment. This increase would be permanent and would be uncorrelated with student outcomes. This ideal scenario is unrealistic and in practice, counseling departments generally exhibit minimal variation.[16] The period following the MHSC grant is advantageous as it produces adequate variation within schools, with additional variation across schools in the exact timing of counseling department changes. Although not the ideal scenario, the ability to exploit within school variation is a significant improvement given the literature. Using all four-year public high schools in California from 2003 through 2015, missing academic year 2009 to 2010, I estimate the following model:

$$Y_{st} = \alpha + \beta\, S - to - C\ Ratio_{st} + \boldsymbol{X}_{st}\delta + \gamma_s + \rho_t + \varepsilon_{st}$$

Y_{st} represents students in school s in year t and is the overall dropout rate or the dropout rate for students in grades 9, 10, 11, or 12, calculated as share of enrolled students who drop out. The coefficient of interest, β, describes the percentage point change in the outcome variable if there is an additional student per counselor.[17]

[16] I discuss variation in CA's schools prior to the grant in the data section.
[17] The qualitative results and their implications for the cost-benefit analysis are robust to using number of counselors as the variable of interest.

Following the temporary increase brought on by the grant, if counseling departments are less likely to reduce their staff in schools with higher shares of academically at-risk students, then the estimates will be biased downward. To account for any time-invariant school characteristics during the sample period, I include school fixed effects, γ_s. The estimates from these models are thus identified by comparing different student-to-counselor ratios within the same school. The inclusion of year fixed effects, ρ_t, controls for annual changes common to all schools and school-specific time-trends address other time- and school- varying unobserved factors. To account for within school correlation of errors, I cluster standard errors at the school level.

$\boldsymbol{X}_{st}$ contains control variables for student and school characteristics that vary over the sample period within schools. Student characteristics include percent Hispanic, percent black, percent Asian, and percent Free and Reduced Price Meals (FRPM). Within-school differences over time are further accounted for with controls for student-to-teacher ratios, enrollment, and enrollment squared. Even with school fixed effects and control variables, the estimates will be biased if changes in counseling programs coincide with changes in other non-counseling resources that affect the outcome variables. I introduce control variables for potential sources of omitted variables below, including school social workers, psychologists, librarians, and nurses.[18]

1.5 DATA AND DESCRIPTIVE STATISTICS

[18] Another consideration is how transfer rates may affect the coefficients of interest. However, the numerators in the outcome variables distinguish between dropouts (or graduates) and transfers. Additionally, the denominator measures enrollment at the beginning of the school-year (a measure that includes all potential dropouts, graduates, and transfers, but not those who have dropped or transferred out yet).

I analyze the relationship between student-to-counselor ratios and student outcomes using data from the California Department of Education (CDE). The final dataset covers all four-year public high schools from 2003 to 2015, missing academic year 2009-10.[19]

1.5.1 High School Outcomes

Annual dropout rates by grade are calculated by dividing the total number of dropouts by total enrollment. Enrollment is measured at the beginning of the academic year and represents students enrolled on that school day. Table 1 contains a detailed list of how dropouts are defined. Local education agencies are required to document all exiting students at the end of the school year with the appropriate exit codes. Dropouts are students who left a public school and were not found enrolled in an education program working toward a diploma.

I restrict the analysis to four-year traditional public high schools. Non-traditional schools include alternative schools of choice, continuation high schools, county community schools, district community day schools, juvenile court schools, and opportunity schools. With high student turnover in these schools and poor data system maintenance, researchers advise great caution when studying these schools as student outcome statistics are highly sensitive.[20]

[19] The data excludes charter high schools. From conversations with school and district officials, charter schools often adopt alternative counseling programs. With that said, the results are robust to including them. Staff demographic data are unavailable from the CDE for academic year 2009-10.
[20] They are sensitive to school resources and administrations, with variation across years. Further, approximately 99 percent of institutions with the School Ownership Code of "High School (public)" are matched to school demographic variables. The corresponding statistic for the alternative institutions is less than 70 percent.

Table 2 presents descriptive statistics for the primary dependent variables of interest. To better describe what share of students drop out or graduate, Table 2 also shows the percentage of entering 12th graders who graduate. The combination of the 12th grade graduation and dropout rates indicate that the vast majority of students graduate or drop out of high school. Dropout rates are largest among 12th grade students with over 4 percent of incoming 12th graders dropping out of traditional high schools. About one percent of entering 11th, 10th, and 9th grade students drop out. With large schools in California, these dropout rates correspond to a large number of dropouts. For example, there were approximately 17,000 dropouts in 2015 alone, a decline from the previous year of 20,000 dropouts. Further, the grade composition of dropouts has changed over time (Figure 1 and Table 2). There are relatively less students dropping out in the first two years of high school. For example, in 2009, 12th grade dropouts accounted for 50 percent of total dropouts, a statistic that increased to 61 percent in 2015. Conversely, 16 percent of total dropouts occurred in 10th grade in 2009, decreasing to 11 percent in 2015. The combination of grade-specific counselor responsibilities and dropout rate compositional changes highlights the need to determine potentially heterogeneous treatment effects.

Finally, the schools in Table 2 account for a large portion of the total number of dropouts in California. For example, in 2015, traditional high schools produced approximately 30,000 dropouts, which is about 60 percent of the total dropouts in the state. During the sample period, traditional high schools produce over 55 percent of total dropouts in California, on average.[21] To add context and emphasize the magnitude of these

[21] Continuation high schools account for 25 percent of total dropouts, followed by alternative high schools at 9 percent.

statistics, California's traditional high schools alone produce more dropouts than all other states. These schools account for over 10 percent of the total dropouts in the country (Stillwell and Sable, 2013).

1.5.2 Counseling Services

To obtain information about school counseling staff, I combine the CDE's Staff Demographic and Staff Assignment Data Files. These data include information about the number of employed administrative, teaching, and pupil support personnel staff. I incorporate school characteristic and demographic information by adding the CDE's Enrollment, English Learners, Free and Reduced Price Meals (FRPM), and Academic Performance Index (API) Data Files.[22]

Figure 2 displays the average number of counselors per high school over time. Prior to 2008, there is little variation in counseling departments. In 2008, there is a large increase, followed by a period of aggregate decline. Specifically, across the entire time period, about 70 percent of schools experience some change in the size of their counseling departments. However, before 2008, out of the 38 percent of schools that had zero to two counselors, about 60 percent never experienced within school changes in counselling. Generally, 50 percent of schools before the grant never experience a change in counseling departments. On the other hand, about 35 percent of schools after the grant do not experience variation within their departments.

The next set of statistics aim to understand the factors that drive counselor variation within schools. Appendix Table A.1 pools four-year public high schools and shows a broad description of school characteristics by the number of employed counselors. There

[22] API statistics are only available through 2012.

is a strong relationship between number of counselors and student enrollment. Not surprisingly, a similar pattern emerges with respect to the number of teachers in the schools, indicating that larger schools employ more staff. In terms of demographics, Table A.1 indicates that there is a positive relationship between number of counselors and percent Hispanic and percent English learners for higher levels of counseling. However, the correlations between number of counselors and these variables are weak. These descriptive statistics follow from ASCA's counselor-to-student recommendations in that counseling is strongly correlated with school size. The recommendations are specific to enrollment and do not consider school demographics or student outcomes.

To further explore the factors that drive counselor variation, I regress number of counselors on school-level variables. Table 3 Column 1 displays the results when the only regressor is enrollment, while Columns 2 through 5 add percent race, percent FRPM, percent English learners, and number of teachers variables (all of the percent variables range from zero to one). The coefficient on enrollment remains statistically significant at the one percent level across all specifications. Enrollment alone explains 51 percent of the variation in the number of counselors. Adding the six other covariates increases the adjusted R^2 by only three percentage points.[23]

The methodology relies on within school variation, which accounts for time-invariant factors. The final specification (Table 3, Column 6) indicates that the number of counselors is uncorrelated with high-minority schools, for example. Rather, there are more

[23] The regression results in Table 3 are largely robust to school enrollment weights. The coefficients on the variable of interest (total enrollment) are unchanged. While some of the magnitudes on the demographic variables increase, the general implications remain unchanged.

counselors in larger schools, and correspondingly, schools with higher English language learner student populations.[24]

1.6 RESULTS

Tables 4 through 7 contain the main results of the paper. Table 4 presents the results using the overall dropout rate as the outcome variable for the entire sample period, before the grant, and after the grant. Tables 5 through 7 use dropout rates by grade as the outcome variables and differ in the sample years. The reported coefficient of interest represents the percentage point change in dropout rates when there is a one student increase per counselor. I present estimates derived from models that include school fixed effects, year fixed effects, and baseline control variables, including percent Hispanic, percent black, percent Asian, percent FRPM, and student-to-teacher ratios.

With school fixed effects, there is a positive relationship between student-to-counselor ratios and the overall dropout rate (Table 4), indicating that increased student caseloads are associated with higher dropout rates. This positive relationship is statistically significant in the post-grant period, where there is increased counselor variation. For example, a 100 student decrease per counselor (resulting in 370 students per counselor) would decrease the overall dropout rate by 1.7 percentage points. Table 4 also displays

[24] Figures A.1 through A.5 show within school variation for a subsample of schools. I randomly select 100 schools and group them into four categories based on average enrollment. Consistent with the previous discussion, the largest schools in the sample employ the most counselors (Figure A.1). These plots generally show that there are no trends in counseling levels within schools, mitigating the concern that trends within schools may be correlated with time-varying unobserved factors. For example, out of the 25 largest schools displayed in Figure A.1, only two show general declines in counseling levels during the time period. Silverado High School and Lakewood High School show declines in counseling for four consecutive years. The remainder of the schools depict fluctuations throughout the six year period. Figure A.1 through A.4 suggest that the declining trend observed in Figure 2 is not reflected within schools, alleviating concerns that time-varying unobserved factors within schools bias the results.

coefficients for another potentially influential school factor, student-to-teacher ratio. All of the models with school fixed effects yield insignificant teacher results. Furthermore, the results are robust and slightly stronger with the inclusion of school-specific time-trends.

ASCA recommends 250 students per counselor. In the post-grant period, there are about 470 students per counselor. If there is a decrease of 220 students per counselor to meet ASCA's recommendations, then the overall dropout rate would be effectively driven to zero. A more conservative and realistic decrease to a ratio of 400 students per counselor would lead to 14 less dropouts per year, compared to the average of 34 dropouts per year.

The next set of tables focus on grade-specific dropout rates. The results for each grade are conditional on passing the lower grade(s). With respect to the sample period studied, grade-specific dropout rate results follow the general patterns observed with the overall dropout rate results. Table 5 indicates a positive relationship between student-to-counselor ratios and grade-specific dropout rates for years 2004 to 2015. However, as seen in Tables 6 and 7 that separate the results by pre- and post- grant, the later years drive the positive results. With school fixed effects, none of the coefficients of interest are statistically significant before the grant. After the grant, there appears to be a counselor effect among students in grades 10 through 12, with the magnitudes increase in grade. Admittedly, results for grades 12 and 10 rely on the inclusion of school-specific time-trends. I do not incorporate these less robust results in the cost-benefit analysis below.

The results above are biased if changes in counseling programs coincide with changes in other non-counseling resources that affect the outcome variables. For example, there may be investments over time in other student support staff, like psychologists or social workers, to replace counselors. Assuming a negative correlation between these staff and dropouts rates, then regressing graduation rates on counselors will produce underestimates. Further, estimates are biased if there are investments in other non-staff related resources, such as after-school library hours. Finally, based on discussions with school counselors, the school administration's general attitude toward student support may affect both counseling and student outcomes. [25] Administration experience could presumably also have an independent effect.

I add control variables to address these potential sources of bias. These variables control for the number of school psychologists, social workers, nurses, and librarians.[26] Assuming that additional services require additional staff, then these controls are, in the least, adequate proxy variables. I also control for the average level of experience of the principal and vice principal(s), under the assumption that those with increased experience may view student support staff differently. Appendix Tables A.2 and A.3 contain the dropout results with these additional covariates. The student-to-counselor estimates are robust, with minimal changes in magnitude in the thousandths places.

An additional concern is that there are other school shocks that affect both counselors and student outcomes that are not captured by the control variables. To better isolate the effects of counselors from other shocks, I use regional variation within the state and introduce county-by-year fixed effects. The results are robust to including these controls. The coefficient of interest when considering the overall dropout rate decreases

[25] There is little empirical evidence to support the claim that the administration's attitudes towards counseling services vary by experience. Rather, this possible relationship is based on conversations with counselors at the School Counselor Leadership Conference hosted by the San Diego County Office of Education.

[26] Based on counselor time-use surveys, counselors do not spend time advocating for changes in staff for other departments. Thus, it is reasonable to assume that social workers, psychologists, and librarians should not be an outcome variables.

slightly from 0.016 to 0.12, but is meaningfully consistent. Similarly, the coefficient for the grade 11 dropout rate result, the most convincing grade-specific result, also decreases slightly from 0.025 to 0.022, but maintains statistical significance.

The final concern centers on whether or not to weight by enrollment. One potential issue is that unweighted smaller schools could have more measurement error in the controls and influence the results. Second, with weights, the estimates are population representative. The dropout and graduation results presented above are generally robust to the inclusion of enrollment weights (not displayed). The magnitudes change slightly, but statistical significance and economic implications are maintained.

1.6.1 Placebo Tests

I conduct two placebo tests. The first test uses performance on the California High School Exit Exam (CAHSEE) as the outcome variable. Students take the CAHSEE for the first time at the beginning of the 10th grade year and are required to pass to earn a high school diploma. Given that students take this exam at the very beginning of the school year, current school counselors have little room for impact. Table A.4 contains these results using the outcome variable percent passed in grade 10, as well as, performance by subject matter. The second placebo test uses the previous year's dropout rates as the outcome variable and Table A.5 contains these results. I use the overall dropout rate and grade-specific dropout rates, and present the results before and after the grant. With one exception, none of the 16 regressions between the two placebo tests yields statistically significant results.

1.7 DISCUSSION

7.1 Mechanisms: Attendance and Disciplinary Outcomes

Establishing mechanisms through which the above graduation and dropout patterns emerge is important as it informs effective counseling program development. Among younger students, researchers find that increases in counseling services improve behavioral issues and attendance rates. If counselors produce similar effects at the high school level, then improvements in discipline and attendance may be mechanisms through which students are encouraged to remain in school. In this section, I briefly describe research about school counseling that considers alternative outcome variables. I supplement the discussion with evidence specific to the current setting and time period.

At the elementary school level, lower student-to-counselor ratios are shown to reduce disciplinary and misbehavior incidents (Carrell and Carrell, 2006; Reback, 2010a; Reback, 2010b; Carrell and Hoekstra, 2014).[27] Papers at the high school level rely on cross-school variation. As I show above, omitting school fixed effects produces opposite results. Nevertheless, these papers generally conclude that more counselors lead to improvements in school attendance and discipline rates.

The California Department of Education provides truancy and disciplinary (expulsions and suspensions) data, available beginning in academic years 2012-2013 and

[27] Carrell and Carrell (2006) study elementary schools in Florida's Alachua County and exploit within-school variation in the number of counselors. They find that lower student-to-counselor ratios reduce both the share of students involved in any disciplinary incident and the likelihood of recidivism. Reback (2010a) exploits discontinuities in Alabama's statewide policy of subsidizing elementary counselors based on discrete enrollment cutoffs. He finds that an additional counselor reduces disciplinary incidents, but has no effect on mean test scores. The first national study of elementary school counselors is conducted by Reback (2010b) and examines how changes in state's elementary school counselor policies over time influence school climate. He finds that adopting a counselor subsidy or minimum counselor–to-student ratio reduces the fraction of teachers reporting student misbehavior. Finally, using the Alachua County data, Carrell and Hoekstra (2014) exploit within-school variation in counselors from the random placement of graduate student counselor interns. They find similar results in that there are positive impacts on boys' test scores and reductions in misbehavior. This group of papers consistently show that counselors play an influential role among young students

2011-2012, respectively. I replicate the above analysis using these outcome measures and present the results in Appendix Table A.6. Truancy and discipline measures report the total number of events, and do not take into account the number of unique individuals. For example, although there are on average 1,700 students in the school, the truancy mean of 716 does not necessarily suggest that 42 percent of students are truant at some point during the school year. I use total counts as the outcome variables.

Without school fixed effects, increases in student-to-counselor ratios are associated with more truant students and less expulsions and suspensions. These results are counterintuitive given the literature at the elementary school level. However, they are very imprecise with these data, and I cannot determine the relevance of these potential sources in explaining the relationship between student-to-counselor ratios and dropout rates.

1.7.2 Cost-Benefit Analysis

The previous section shows that increasing high school counselors leads to reductions in dropout rates. I now consider the economic implications associated with hiring more counselors. Along with other states, the recent fiscal environment has forced California to rethink its K-12 expenditure allocations. Thus, although increasing counselors may reduce the dropout rate, it is important to establish the direct costs and benefits.

Educational, guidance, school, and vocational counselors in California earn approximately $60,000, on average, while starting salaries typically range from $32,000 to $40,000 per year.[28] The CDE provides selected salary statistics for public employees. I compile these data to account for total spending on guidance counseling, including all

[28] 21-1012 Educational, Guidance, School, and Vocational Counselors. (n.d.). Retrieved October 26, 2016, from http://www.bls.gov/oes/current/oes211012.htm

benefits. Guidance counselor salaries make up 86 percent of total counseling expenditures. To account for full counselor costs, I assume a per counselor cost of $60,000, which translates to $35 per pupil, on average. To achieve the previously discussed student-to-counselor ratio of 400 to one, each school would need to invest about $10,000 in their counseling departments, assuming no changes in enrollment.

The economic benefits of reducing dropout rates occur further in the future and are well-established in the literature. All figures in this section are presented in 2015 dollars. Rouse (2005) finds that the discounted present value of the lifetime difference in income between an individual who does not graduate high school and one who does (but completes no further schooling) is about $316,000. She also shows that the lifetime difference in income tax payments alone is $73,000. Including Social Security contributions, a high school dropout will contribute nearly $119,000 less in federal and state taxes than a high school graduate and about $273,000 less than an individual with at least a high school degree. Levin et al. (2007) estimate the social cost of high school dropouts at about $256,000. Similarly, Belfield and Levin (2007) show that each additional high school graduate contributes net fiscal lifetime benefits of $136,600 to the federal government, and $63,000 to California's state and local governments. They further show that the social gains from inducing a potential high school dropout to graduate generates up to $392,000. [29]

These studies estimate the costs associated with the average dropout and it is unclear if changes in student-to-counselor ratios will affect the average dropout. With that said, a student-to-counselor ratio of 400 to one results in 14 less dropouts per school year.

[29] Rouse (2005), Levin et al. (2007), and Belfield and Levin (2007) all use discount rates of 3.5 percent.

With a per school cost of $10,000, each prevented dropout must yield a social benefit of less than $1,000 to break even. Thus, it is very likely that reductions in student-to-counselor ratio will results in net social benefits.

1.7.3 How do counseling results compare to other interventions?

To put the dropout results into context, I discuss other large-scale interventions that improve high school graduation outcomes. The Institute of Education Sciences presents six recommendations to reduce dropout rates, which are categorized into three groups: identifying dropout problems, targeted interventions, and school wide reforms.[30] Table A.6 lists papers that fit in these categories, organized by age of intervention. I focus on policy impact evaluations with plausible identification strategies that find effects on the high school graduation or dropout rate.[31] The costs are $14,069 per student and $73,103 per additional graduate. These costs are significantly greater than the costs per student and graduate associated with counselor increases.

Among the early childhood interventions, Head Start is the largest publicly funded program that serves over 900,000 disadvantaged children offering a variety of services, including preschool education. The papers listed in Table A.6 study different populations, but all indicate declines in dropout rates. The declines range from 3 to 20 percentage

[30] Recommendations include using data systems to identify at-risk students, assigning adult advocates to at-risk students, providing academic support and enrichment, implementing classroom specific programs targeting behavioral and social skills, personalizing the learning environment, and providing instruction to better engage students (Dynarski, et al. (2008).
[31] I do not discuss interventions that find an effect on test scores, but not on dropout or graduation rates.

points, corresponding to 4 to 25 percent (Ludwig and Miller, 2007; Garces, et al., 2002; Deming, 2009).[32]

The Tennessee Student/Teacher Achievement Ratio (STAR) Experiment provides an experimental setting to study the effects of elementary school classroom size and quality on dropout rates.[33] Murnane (2013) shows that the magnitude of the effect of class quality on graduation rates is approximately the same among children enrolled in regular size kindergarten classes as among those enrolled in small classes (12 to 15 percent).[34] Krueger (2002) estimates that the costs per pupil for small classes is $10,092, which significantly exceeds the counselor costs per pupil.

At the middle school level, researchers study how the grade of elementary-to-middle school transition affects high school outcomes. For example, Bedard and Do (2005) find that moving from a system in which students change schools at the end of grade 6, as opposed to grade 5, reduces the high school graduation rate by 1 to 3 percent. Schwerdt and West (2013) show that students enrolled in one K-8 school, as opposed to changing schools at the end of grades 6 and 8, have slightly lower dropout rates. This finding highlights the need for counselors to assist in these transitions. Furthermore, although the

[32] Other early child intervention evidence come from small scale preschool programs including Perry Preschool and the Abecederian programs. These programs find positive impacts on high school female graduation rates (Heckman, et al. (2010), Murnane (2013)). Chicago's Child-Parent Center Education program provides three to nine year old low-income children intensive education and family-support services. Graduation rates among students who participate in the CPC are 7.7 percentage points higher than the matched control group (Reynolds, et al. (2011)).

[33] In the mid-1980s, over 11,000 students and 1,300 teachers in Tennessee public schools participated in the STAR experiment. Children entering kindergarten were randomly assigned to a small class with 13 to 17 children or to a regular size class with 22 to 25 students. Teachers in each school were also randomly assigned to classrooms

[34] Chetty, et al. (2011) find that students assigned to high value-added teachers in grades four to eight are more likely to attend college. Although they do not show the impacts directly on graduation rates, it is likely that some of the positive effects are driven by increases in the high school graduation rate.

costs to change transition grades within a school district are not calculated in the literature, they are likely substantial as they involve large-scale administrative and logistical changes.

Deming et al. (2011) show that students from low quality neighborhood school zones who enroll in public high schools of their choice are about 9 percentage points more likely to graduate from high school (16 percent). There are two additional studies at the high school level that involve wide-scale school reform. The Talent Development High School Model targets schools that serve many low-achieving minority students and places students in learning communities of 100 to 125 students taught by the same four or five teachers. Kemple, et al. (2005) find 8 percentage point increases in the on-time graduation rate. Alternatively, starting in 2002, New York City replaced more than 20 low-performing high schools with more than 200 smaller schools. Using lotteries that determined access to small schools, Bloom et al. (2010) show improvements in graduations rates by 9 percentage points or 15 percent.

Considering the above interventions, this paper's findings are at the higher end. This result is not surprising given that one of the primary responsibilities of counselors is to identify and work with at-risk youth. The discussed interventions also indicate that there are a variety of factors that may reduce dropout rates. However, hiring an additional counselor is arguably the least burdensome. For example, reducing classroom sizes, breaking up larger schools, or altering the age at which students change schools requires great logistical planning and are costly to implement. Hiring counselors aligns with many of the principles associated with the school-wide reforms. Researchers identify strong leadership, student support, and improvements in school culture as important components in the success of these school-wide reforms. Campus guidance counseling services may serve as important channels through which these improvements are achieved.

1.8 CONCLUSION

This paper is the first to estimate a plausibly causal effect of high school guidance counselors on dropout and graduation rates. Specifically, it enhances the existing literature that uses cross-school variation by introducing panel data methods. Using data on all public high schools from the California Department of Education, I employ difference-in-differences methods to exploit within school variation in the number of employed counselors. The analysis finds that decreases in the student-to-counselor ratio are associated with decreases in dropout rates. For example, a 100 student decrease in the student-to-counselor ratio would decrease the overall dropout rate by 1.7 percentage points. Using these estimates, I show that under conservative assumptions, the costs association with decreases in the student-to-counselor ratio are offset by the social benefits.

Table 1.1: Dropout Classification Rules

Non-Dropout	
Graduated with a High School Diploma.	Moved to another country.
Graduated students with disabilities with waiver and passed the California High School Exit Exam with modifications.	Enrolled in Adult Education and received a diploma.
Graduated students with disabilities with waiver and is exempt from passing the California High School Exit Exam.	Enrolled in Adult Education and is working towards General Educational Development or diploma.
Student with exceptional needs received a certificate indication they met the requirements of Education Code section 56390.	Entered college and is working towards a college degree - with documentation.
Exited a Special Education transition program and was a completer.	Entered a health care facility.
Died.	Completed General Educational Development.
Transferred to another California public school - with documentation.	Passed California High School Proficiency Exam.
Transferred to another California public school for disciplinary reasons - with documentation.	Entered an institution not primarily academic in nature (military, job corps, etc.) but is in a program working towards a diploma.
Transferred to another California public alternative education or independent study school.	Left for medical reasons.
Enrolled in a private school in California - with documentation.	Infant, Pre-K, K-6 - withdrew from the school.
Enrolled in a public or private school in the U.S. - with documentation.	Student was pre-enrolled in a school but did not show and is not a N420 (Completed a school year but did not return to that school).
Reached maximum age - without enough credits.	Matriculated to another school.
Summer or Intersession Exit - expected to return to the same school after the break.	
Dropout	
Left school, passed all requirements except for California High School Exit Exam.	
Left school and not known to be enrolled in an education program working towards a diploma. Includes students who left for a job, marriage, etc.	
Enrolled in an Adult Education program but has subsequently dropped out of the program.	
Withdrawn for disciplinary reasons but did not arrive at the destination educational institution.	
Completed grade 12 but did not graduate or receive a diploma and not in an academic program working towards a diploma.	
Entered an institution not primarily academic in nature (military, job corps, etc.) and is in a program not working towards a diploma.	
Other (unknown reason).	
Completed a school year but did not return to that school.	
To home school setting not affiliated with a private school independent study program at a public school.	

Table 1.2: High School Outcome Variable Descriptive Statistics

	Traditional Four-Year High Schools					
	2003-04 to 2005-06			2007-08 to 2014-15		
	mean (%)	sd	N	mean (%)	sd	N
Annual Measure						
Overall Dropout Rate	1.81	2.17	3394	1.88	2.41	6475
Grade 12 Dropout Rate	4.09	5.37	3292	4.70	9.58	6361
Grade 11 Dropout Rate	1.66	6.01	3337	1.43	2.88	6420
Grade 10 Dropout Rate	1.48	17.30	3374	1.05	2.27	6448
Grade 9 Dropout Rate	1.22	2.10	3375	0.95	3.40	6438
Grade 12 Graduation Rate	87.96	28.92	3308	89.92	25.38	6361
% of Total Dropouts in State	59.0			55.0		

Notes: Traditional four-year schools are those with the School Ownership Code "High School (Public)." These exclude alternative schools of choice, continuation high schools, county community schools, district community day schools, juvenile court schools, and opportunity schools. Annual dropout rates measure the number of dropouts throughout the year divided by the number of students enrolled at the beginning of the academic year. Grade 12 Graduation Rate is the share of enrolled 12th grade students who graduate. Descriptive statistics are displayed separately for the pre-grant years (2003-04 through 2005-06) and post-grant years (2007-08 through 2014-15, missing 2009-10).

Table 1.3: School Characteristics and Variation in Counseling

Outcome: # Counselors (mean=4)	(1)	(2)	(3)	(4)	(5)	(6)
Total Enrollment	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Hispanic		1.123***	-0.093	-1.345***	-1.178***	1.415*
		(0.176)	(0.218)	(0.341)	(0.334)	(0.843)
% Black		0.691	-0.361	-0.363	-0.321	-1.457
		(0.485)	(0.517)	(0.506)	(0.497)	(1.872)
% Asian		0.177	-0.145	-1.956***	-1.859***	-0.647
		(0.434)	(0.429)	(0.603)	(0.577)	(1.320)
% FRPM			1.517***	1.320***	1.107***	1.060***
			(0.238)	(0.247)	(0.241)	(0.332)
% English Learner				2.636***	2.512***	0.552
				(0.494)	(0.478)	(0.579)
# Teachers					0.003***	0.001***
					(0.001)	(0.000)
Constant	0.247***	-0.239**	-0.469***	-0.344**	-0.427***	
	(0.086)	(0.121)	(0.141)	(0.138)	(0.140)	
School, Year Fixed Effects						x
Observations	10192	10192	9365	9065	9065	9049
Adjusted R-Square	0.501	0.513	0.522	0.515	0.524	0.771

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses and are clustered at the school level.

Table 1.4: Overall Dropout Rate Results

Outcome Variable:	Overall Dropout Rate								
	All Years			2003-04 through 2006-07			2007-08 through 2014-15		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Student-to-Counselor Ratio	-0.018***	0.004	0.012	-0.018	0.003	0.046	-0.015**	0.017**	0.023**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.018)	(0.036)	(0.007)	(0.008)	(0.010)
Student-to-Teacher Ratio	-0.511	6.564	3.73	-9.174**	0.681	10.833	2.664	10.814	5.479
	(7.202)	(7.153)	(3.642)	(3.613)	(5.342)	(13.559)	(9.178)	(9.841)	(5.219)
Enrollment	0	0.000***	0	0.000***	-0.000*	0	0	0.001***	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Baseline Covariates	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x
School Fixed Effects		x	x		x	x		x	x
School Specific Trends			x			x			x
Observations	8504	8482	8482	2259	2184	2184	6245	6221	6221
Adjusted R-Square	0.305	0.606	0.635	0.364	0.669	0.746	0.291	0.61	0.672

Notes: * p<0.10, ** p<0.05, *** p<0.01. Dropout rates are the share of students who dropout during the school. Baseline covariates include percent Hispanic, percent Asian, percent black, percent free and reduced price meals, enrollment squared, and student-to-teacher ratios. Standard errors are in parentheses and are clustered at the school level. Results are displayed separately for the pre-grant years (2003-04 through 2005-06) and post-grant years (2007-08 through 2014-15, missing 2009-10).

Table 1.5: Dropout Rate by Grade Results, All Years

Dropout Outcome Variable:	Grade 12			Grade 11			Grade 10			Grade 9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Student-to-Counselor Ratio	-0.046***	-0.016	0.017	-0.005	0.045*	0.054*	-0.011**	0.007	0.017**	-0.009	0.008	0.011
	(0.016)	(0.021)	(0.030)	(0.010)	(0.025)	(0.032)	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
Student-to-Teacher Ratio	-8.609	2.022	2.509	2.945	14.513*	12.072*	2.176	6.691	1.813	11.881	13.45	1.516
	(10.273)	(10.148)	(7.206)	(6.685)	(8.196)	(6.883)	(5.649)	(5.958)	(3.145)	(15.067)	(13.663)	(2.027)
Enrollment	0.000***	0	-0.002	0	0	-0.001	0	0.000***	0	-0.000**	0	0
	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Baseline Covariates	x	x	x	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x	x	x	x
School Fixed Effects		x	x		x	x		x	x		x	x
School Specific Trends			x			x			x			x
Observations	8340	8324	8324	8430	8408	8408	8479	8459	8459	8462	8437	8437
Adjusted R-Square	0.107	0.237	0.556	0.077	0.18	0.313	0.195	0.415	0.428	0.076	0.384	0.713

Notes: * p<0.10, ** p<0.05, *** p<0.01. Dropout rates are the share of students who dropout during the school by grade. Baseline covariates include percent Hispanic, percent Asian, percent black, percent free and reduced price meals, enrollment squared, and student-to-teacher ratios. Standard errors are in parentheses and are clustered at the school level. Results are displayed separately for the pre-grant years (2003-04 through 2005-06) and post-grant years (2007-08 through 2014-15, missing 2009-10).

Table 1.6: Dropout Rate by Grade Results, 2003-04 through 2006-07

Dropout Outcome Variable:	Grade 12			Grade 11			Grade 10			Grade 9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Student-to-Counselor Ratio	-0.099***	-0.049	-0.01	0.02	0.006	0.035	-0.003	0.029	0.069*	0.003	0.016	0.058
	(0.028)	(0.041)	(0.073)	(0.026)	(0.023)	(0.042)	(0.009)	(0.018)	(0.038)	(0.010)	(0.019)	(0.038)
Student-to-Teacher Ratio	-26.839**	-4.513	1.795	10.188	-4.939	2.723	-4.551	-1.049	6.662	1.157	6.475	19.265
	(12.609)	(9.999)	(18.626)	(17.474)	(6.888)	(15.701)	(2.830)	(4.664)	(12.893)	(4.009)	(9.009)	(19.353)
Enrollment	0.001***	-0.002*	0.002*	0	0	0	0.000**	0	0	0	0	-0.001*
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Baseline Covariates	x	x	x	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x	x	x	x
School Fixed Effects		x	x		x	x		x	x		x	x
School Specific Trends			x			x			x			x
Observations	2194	2116	2116	2225	2144	2144	2250	2174	2174	2247	2172	2172
Adjusted R-Square	0.296	0.666	0.748	0.035	0.578	0.675	0.318	0.56	0.647	0.244	0.486	0.594

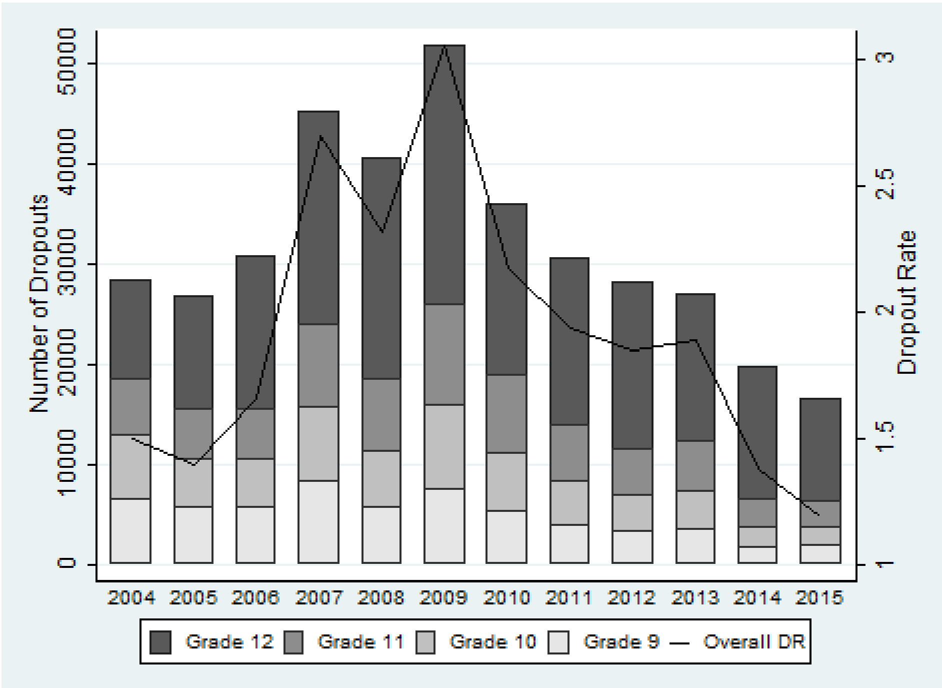
Notes: * p<0.10, ** p<0.05, *** p<0.01. Dropout rates are the share of students who dropout during the school by grade. Baseline covariates include percent Hispanic, percent Asian, percent black, percent free and reduced price meals, enrollment squared, and student-to-teacher ratios. Standard errors are in parentheses and are clustered at the school level.

Table 1.7: Dropout Rate by Grade Results, 2007-08 through 2014-15

Dropout Outcome Variable:	Grade 12			Grade 11			Grade 10			Grade 9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Student-to-Counselor Ratio	-0.016	0.03	0.091**	-0.016*	0.026**	0.034**	-0.012**	0.005	0.013**	-0.011	0.01	0.007
	(0.017)	(0.026)	(0.044)	(0.009)	(0.011)	(0.014)	(0.006)	(0.006)	(0.007)	(0.010)	(0.008)	(0.007)
Student-to-Teacher Ratio	-3.23	8.247	2.469	0.964	9.697*	7.365**	4.924	8.87	4.511	16.425	19.757	0.976
	(12.049)	(13.476)	(9.384)	(6.847)	(5.652)	(2.933)	(7.204)	(8.272)	(4.360)	(20.090)	(19.596)	(2.066)
Enrollment	0	-0.001	-0.005	-0.000*	0.001***	-0.001	-0.000***	0.000***	0	-0.000**	0	0
	(0.000)	(0.002)	(0.005)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Baseline Covariates	x	x	x	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x	x	x	x
School Fixed Effects		x	x		x	x		x	x		x	x
School Specific Trends			x			x			x			x
Observations	6146	6129	6129	6205	6182	6182	6229	6207	6207	6215	6189	6189
Adjusted R-Square	0.087	0.172	0.515	0.146	0.426	0.477	0.168	0.384	0.467	0.056	0.377	0.804

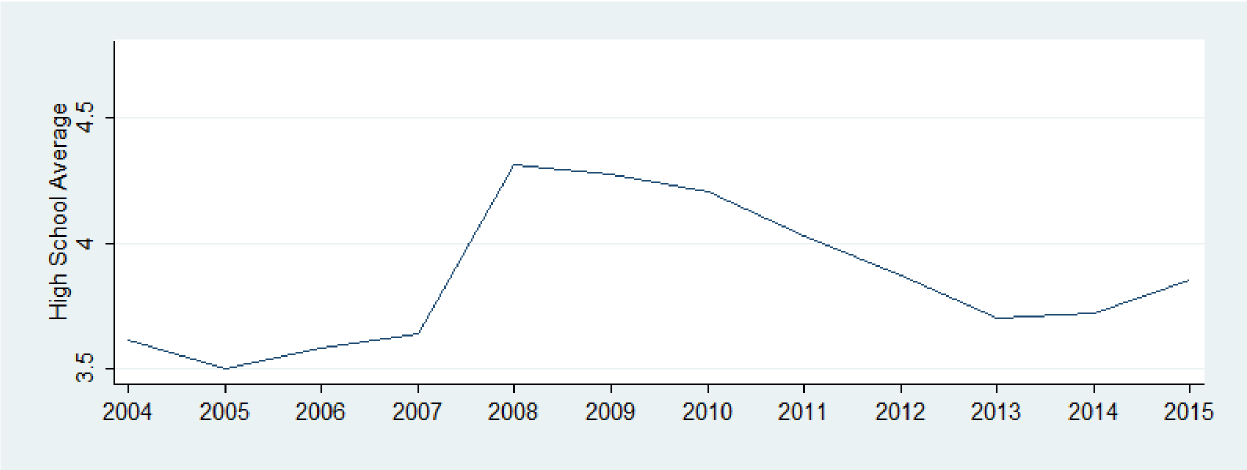
Notes: * p<0.10, ** p<0.05, *** p<0.01. Dropout rates are the share of students who dropout during the school by grade. Baseline covariates include percent Hispanic, percent Asian, percent black, percent free and reduced price meals, enrollment squared, and student-to-teacher ratios. Standard errors are in parentheses and are clustered at the school level.

Figure 1.1: Total Number of Dropouts, Overall Dropout Rate, and Dropouts by Grade



Notes: Figure 1 shows statistics for traditional high schools with the School Ownership Code "High School (Public)." There are approximately 900 non-charter schools between academic years 2003-2004 and 2014-2015. Overall dropout rate is measured as the number of dropouts throughout the year divided by the number of students enrolled at the beginning of the academic year in the school. Dropouts do not include students who transferred to another public school or district.

Figure 1.2: Average Number of High School Counselors per School over Time



Notes: Averages are displayed for traditional high schools with the School Ownership Code "High School (Public)." Academic year 2009-10 is an average between 2008-09 and 2010-11.

CHAPTER 2

When Does the STEM Gender Gap Emerge?

Evidence from Science Fairs

2.1 INTRODUCTION

For decades, the gender gap in science, technology, engineering, and mathematics (STEM) fields has caused concern among policymakers and researchers (Sweeney, 1953; Fennema & Sherman, 1977; Goldin, 1994; Hausmann, Tyson, & Zahidi, 2008). Growing worry has prompted calls for the U.S. education system to produce more female graduates with training and expertise in STEM fields (Toulmin & Groome, 2007; Olson & Riordan, 2012). Yet, while female enrollment in high school math and science courses increases, and female performance on math tests improves, female participation in the STEM labor force has remained constant at 24 percent since 2000 (Beede et al., 2011).

Policymakers use the lack of progress in reducing the STEM gender gap to motivate a shift toward targeting K-12 students to increase STEM interest (Venkataraman, Olson, & Riordan, 2010). However, disagreement on when the STEM gender gap emerges makes developing effective policy difficult (Subrahmanyan & Bozonie 1996; Blickenstaff, 2005). The lack of agreement is due to shortcomings in conventional gender gap measures including standardized test scores, classroom performance, and classroom enrollment. Standardized test scores produce mixed results, depending on the year, age group, and exam (Ellison & Swanson, 2010). More importantly, exams do not measure, nor do they claim to measure, a student's interest in a STEM field (Popham, 1999). Classroom enrollment options are limited and generally only available to high school juniors and seniors, reducing the ability to capture gender differentials across STEM fields or among younger students (Hill, Corbett, & St. Rose, 2010). Further, college admission requirements incentivize students to perform well on exams and in classrooms (Clinedinst, Koranteng, & Nicola, 2014), reducing the ability to identify student interest. Collectively, these measures fail to explain the timing of the STEM gender gap.

In this paper, I create a novel STEM gender gap measure to document the age profile of gender differentials. To do so, I construct a dataset of high school and middle school science fair projects at the California State Science Fair (CSSF). I use students' project choices to measure gender gaps.

This gender gap measure has three advantages. First, the CSSF allows for a wide range of projects, allowing the study of gender gap emergence age for a variety of fields. Second, with over 17,000 participants between 1990 and 2014 and approximately 60 percent middle school representation, I study students earlier in their academic careers. Third, the category in which a student competes is determined by his or her choice of project and although the incentive to perform well for college admissions still exists, it is less clear why it would drive the field of study. Thus, compared to conventional gender gap measures, CSSF participation is an improved measure of a student's STEM interest.

The analysis produces two main findings. First, I find significant gender gaps in middle school. For example, middle school females are 29 percentage points less likely to compete in a math field and 35 percentage points less likely to compete in a technology field, relative to social science. Second, gender gaps generally increase from middle school to high school. High school females are 37 percentage points and 42 percentage points less likely to compete in math and technology, respectively.

This paper's findings have two policy implications. First, large gender differentials among middle school students suggest that efforts to reduce the STEM gender gap may be best targeted during elementary school or earlier. Second, policymakers should consider the widening of the gap from middle school to high school to prevent females from dropping out of the STEM pipeline.

The remainder of the paper proceeds as follows: Section 2 describes the literature and Section 3 discusses the newly constructed data set. In Section 4, I present the methodology and follow with the main results in Section 5. Section 6 discusses threats to identification, compares this paper's results to another gender gap measure, explores changes in gender gaps over time, and addresses interpretation in the context of changing samples. Finally, I conclude in Section 7.

2.2 FINDINGS ON THE EMERGENCE OF THE STEM GENDER GAP

The STEM gender gap literature draws from two primary sources of information on high school and middle school performance: standardized test scores and classroom outcomes. I present the overall findings of each and discuss shortcomings to support the use of science fair projects as an alternative and improved source of information.

2.2.1 Test Score Findings

Between the two gender gap measures, standardized test scores are more commonly studied. The National Assessment of Educational Progress (NAEP), a nationally representative sample, is the primary resource supported by the U.S. Department of Education. Perie, Moran, and Lutkes (2005) provide a long-term assessment of gender differences for students ages nine, 13, and 17. Until the late 1980s, nine year old females score slightly higher on the mathematics exam. Among 13 year olds, males start to outperform females in the early 1980s, while males in the oldest age group consistently score higher since 1973. In 2004, the gender gap is significant only for students ages 13 and 17, suggesting that gender gaps in test scores emerge toward the end of middle school. Two additional exams include the Scholastic Aptitude Test (SAT) and American College Testing (ACT) exams. Males outperform females on the quantitative section of the SAT continuously since 1972, on average. Similar results hold for the quantitative section of the ACT, however, both SAT and ACT average differences are small in magnitude (Halpern et al., 2007).

Hyde, Fennema, and Lamon (1990) perform a meta-analysis of 100 studies and find that the math gender gap for the general population is trivial. Further analysis shows a female advantage in computation in elementary and middle school, and no gender differences in understanding of concepts at any age. Relatively large gender differences favoring males in complex problem solving skills emerge in high school. Hyde et al. (2008) conclude that the general population no longer shows differences in math skills, challenging the previously discussed findings using the NAEP data.

Researchers often compare U.S. test scores to international data to motivate a discussion about how social differences affect the emergence and evolution of gender gaps. Although social influence is outside the scope of this paper, the two most common sources, the Program for International Student Assessment (PISA) and the Trends in International Mathematics and Science Study (TIMSS), reveal patterns consistent with the findings that gender differences do not exist. For example, Lemke et al. (2001) find insignificant gender differences in TIMSS scores in the United States. Lindberg et al. (2010) perform a meta-analysis of the 2003 TIMSS and the PISA, representing 493,495 students, and find that all of the mean mathematics effect sizes are very small.

2.2.2 Classroom Findings

The second gender gap information source, classroom outcomes, describes how males and females differ in classroom subject choices and their performance in those classes. Since 1994, high school girls earn more math and science credits and achieve higher grades. For example, among U.S. high school students, 66 percent of females compared to 58 percent of males enroll in chemistry, 93 percent of females compared to 89 percent of males enroll in biology, and 71 percent of females compared to 65 percent of males enroll in Algebra II. However, larger shares of male students take Calculus (12 percent of males compared to 11 percent of females) and physics (34 percent of males compared to 29 percent of females). Advanced Placement (AP) and Honors course enrollment data also shows an overrepresentation of females in math classes (54 percent) and science classes (56 percent), however, males are more likely to take the AP exam and score four percent higher on AP Calculus exams and six percent higher on AP science exams (Freeman, 2005; College Board, 2005, 2007).

2.2.3 Current Gender Gap Measure Issues

Standardized test scores, classroom performance, and classroom enrollment measures of the gender gap are limited in their abilities to capture student interest, which is correlated with future occupation. Studies that establish the important role of interest include Tai et al. (2006). They use the National Education Longitudinal Study of 1988, where eighth-grade students are asked about the career they desire at age 30, and find that students who report science interest are three times more likely to obtain a college degree in a science field. The study does not discuss differences by gender. Maltese and Tai (2010) interview 116 scientists and graduate students in chemistry and physics and find that over 65 percent of male and female participants report interest starting before middle school. The purpose of the study is to establish that interest in science plays a role in future occupations, not to discuss gender differentials.

Although new test score estimates garner considerable attention, most findings produce relatively small gender differences. Thus, exams provide little practical importance in learning about when the gender gap emerges (Ellison & Swanson, 2010). Further, Weinberger (2005) shows that less than one-third of college-educated white males in STEM occupations have high school SAT quantitative scores above 650 (out of 800). She concludes that gender differentials in the workforce cannot be explained by standardized test differentials. Others make similar statements and explain that exams are designed to measure student knowledge, not interest. A recent National Research Council (2011) report states that although difficult, it is critical to measure student interest and motivation, creativity, or commitment and "not just good test takers."

Incentivizes to perform well for college admission boards complicate the ability to measure gender gaps in interest using test scores, classroom enrollment, and grades. The National Association for College Admission Counseling (NACAC) lists grades, particularly in difficult classes, and standardized admission tests among the top factors in admission decisions. Thus, enrollment in higher level quantitative courses and performance may be a better indicator of the desire to go to college, rather than interest in a particular field.

Classroom enrollment statistics of gender gaps are further complicated by state graduation requirements. For example, during the time period studied in the paper, students in California generally follow the "traditional pathway" which consists of Algebra I, Geometry, Algebra II, Pre-calculus, AP Calculus or AP Statistics. Students in California must complete at least two math courses in high school, with one or a combination of courses meeting or exceeding Algebra I rigor (California Department of Education, 2014). Students are often encouraged to follow a predetermined series of classes, which restricts the ability to measure student interest in a subject. Additionally, subject choices are often reserved for older students and are limited in the number of options. For example, among the 2013 high school graduating class, 88 percent of AP biology exams are taken in 11^{th} or 12^{th} grades. AP Calculus had 98.5 percent and AP Chemistry had 93.3 percent of students take the exam in their last two years of high school.

2.2.4 Science Fair Advantages

By the above test score measures, gender gaps in the general population do not exist today, while classroom enrollment suggests that they may emerge in 11^{th} and 12^{th} grades, leading policymakers to perhaps erroneously conclude that gender gaps do not exist prior to the end of high school. CSSF project choice is an improved source of gender gap information because it is not subject to the limitations outlined above. First, the category in which a student competes in is determined by a student's choice of project, reflecting interest in a STEM field. The CSSF explicitly states that one of its objectives is to stimulate interest and recognize students for their efforts. A potential concern is that the choice of project is also motivated by a desire to get into college. For example, students may choose to participate in more difficult categories strictly to improve their college admission prospects, not because they are interested in the topic. Although the incentive to perform well for college admission boards exists at the CSSF, it is less clear that student project type would be influenced, especially compared to advanced courses, which are explicitly favored by admission boards.

Given the standard of quality at the CSSF, I argue that this is not the case. In order to participate in the CSSF, students must receive an offer from their regional fair. Most regional fairs are structured similarly to the CSSF in that students are interviewed by several judges to showcase their knowledge, genuine interest, and enthusiasm for their work. Thus, a CSSF project is an improved measure of student interest. Second, as I discuss in the next section, the large sample of middle school students at the CSSF allows for the study of younger students. Finally, with a large range of categories to compete in, I measure gender differentials in each STEM field, category, and compare those values to existing measures.

2.3 DATA

I construct the CSSF dataset using publicly available individual-specific information from 1990 through 2014. Each year has information for every CSSF participant, including name, grade, division, category, school, and county.

Participant gender is not explicitly stated. To determine gender, I use data from a 100 percent sample of Social Security card applications for U.S. births. In a given year, the Social Security Administration (SSA) records the number of males and females born with a name and reports frequency counts of those names by sex, as long as the name is at least two characters long with a frequency of at least five. I use the student's grade and year of participation to estimate his or her birth year. I then match the student's first name to the SSA data in his or her birth year to determine gender (I assume that participants' current names represent the gender they identify with). If a name applies to both males and females, I assign the majority gender as long as at least 90 percent of children born with that name have the same gender. This method assigns gender to 86 percent of participants. The paper's results are robust to alternative cutoffs of 85 and 95 percent. The less conservative cutoff of 85 percent increases the sample by 124 students and the 95 percent cutoff decreases the sample by 466 students.

I assign gender to half of the remaining 2,651 participants using individual portraits which become available in 2005. Approximately 51 percent of the gender entries identified through photos are female. The paper's results are robust to excluding these individuals. In total, there are 17,265 participants with identified gender.

Middle school students in grades six through eight compete in the Junior Division, while high school students in grades nine through 12 compete in the Senior Division. The number of Junior Division participants generally increases over the 25 year period (Figure 1). Senior Division participation exhibits an increase in earlier years, declines in the late 1990s, and remains relatively stable after with an average of 245 students per year. There are always fewer Senior Division participants in each year.

Within division, students are further divided into categories based on their projects. The number of categories grows over time. In 1990, there are 13 Senior Division Categories and 13 Junior Division categories. By 2014, there are 14 categories for Senior Division projects and 22 categories for Junior Division projects. Categories are renamed, combined, or divided in response to changes in participation. I use the CSSF descriptions of yearly changes to make categories constant over time, when applicable. For example, in 2002, the CSSF renames biochemistry to biochemistry/molecular biology. I combine both categories under the second title. Figure 2 displays number of participants by category.

Using the Economics and Statistics Administration's STEM definitions, I group categories into the four STEM fields. For example, biology is labeled "science," while environmental engineering is labeled "engineering." The majority of students compete in a STEM category, with the highest concentration in science, followed by engineering. Math and technology fields are the least popular (Table 1 and Figure 2). Appendix Table 1 lists the categories with brief descriptions.

2.4 METHODOLOGY

In the following section, I show female participation trends in Figure 3. Gender gap patterns are clear through the figure, however, to estimate significance and the significance of changes across age, I use the following specification:

$$Y_i = \alpha + \beta Gender_i + X_i\gamma + \varepsilon_i$$

where $Gender_i$ is an indicator that equals one if student i is female. I am interested in the magnitude of β for Junior and Senior Division participants and if changes across age are significant. Y_i represents several outcome variables. The first is an indicator that equals one if the student competes in a STEM field and zero otherwise. Second, I create outcome variables to compare each STEM field against non-STEM categories. Third, I create three indicators comparing technology, engineering, or mathematics against science. Largely driven by biology and chemistry, science exhibits the most balanced gender composition and is thus used as the comparison group to study within STEM variation.

CSSF participants represent counties throughout California. To account for time-invariant gender norm differences across California on the relative number of females in STEM, X_i includes student county dummies. I also include year dummies to reduce bias.

There are three additional sources of bias that challenge the claim that CSSF gender gaps reflect differences in interests. The first two are created by the qualification process, which dictates that CSSF participants are students who participate, win, receive a CSSF offer, and accept a CSSF offer at their local county science fairs. First, bias due to gender-specific student self-selection potentially exists at two levels: county fair participation and CSSF offer acceptance. Second, bias due to gender-specific selection by judges exists at the remaining qualification levels: county fair winners and CSSF offers. The third source of bias is due to changing yearly samples of students.

Gender-specific student self-selection at the county level, if relevant, results in CSSF gender gap estimates that are biased downward. Niederle's (2014) summary paper finds that after controlling for a variety of characteristics, gender gaps in tournament entry in stereotypical male tasks persist. Additionally, Niederle and Yestrumskas (2008) find that, conditional on performance, females shy away from difficult and challenging tasks more than males.

Although field experiments produce less conclusive results compared to lab experiments, if gender-specific reactions to competing in male-dominated fields holds in this setting, then the gender gaps observed at county are underestimates. If county science fair participation becomes part of the school curriculum, for example, then the females who would otherwise not compete, would likely enter in less male-dominated fields, increasing the gender gap.

Gender-specific student self-selection from county to state, however, would result in overestimates of gender gaps. If females are more likely to decline an offer to the CSSF, especially if they would have to compete in male-dominated fields, then this paper's findings are biased upward.

The direction of bias due to gender-specific selection by judges is unclear. Consider the two extreme cases. In scenario one, there are no gender gaps at the county-level, but large gaps at the CSSF, while the opposite holds in scenario two. Thus, CSSF gender gaps are a result of who wins and who is selected to receive an offer, reflecting differences in factors other than interests, like performance or judge discrimination.

Finally, the long time period may mask underlying trends about the evolution of gender gaps over time. For example, any gender gaps observed with the pooled data may be driven by results in the earlier time period producing misleading conclusions. Further, any observed gender gap changes during this time period may be due to changes in the underlying mechanisms that determine gender gaps or due to changing samples.

In order to ease estimation concerns due to the qualification process, I construct a county-level dataset and evaluate gender gaps at lower levels. I repeat the above regression analysis and discuss findings below. To evaluate if gender gaps change over time, I estimate β by five-year intervals. I choose five-year intervals to overcome small sample sizes in the year-to-year samples and test the null hypothesis that β_t is equal to β_{t-1}. Additionally, I interact $Gender_i$ with $Year$ and test for a non-zero time-trend. I discuss interpretation in the context of changing samples below.

2.5 SCIENCE FAIR GENDER GAPS

Female participation patterns are displayed in Figure 3. A value of zero indicates balanced gender composition. Negative values indicate an underrepresentation of females and bar heights correspond to the percentage point difference between female and male participation. Among all CSSF participants, male and female participation is balanced, with differences less than two percentage points (Figure 3, Panel A). Figure 3, Panel B further divides students by whether they compete in a STEM category. STEM fields are generally balanced, while non-STEM fields are dominated by females. There is also large increase in female representation from the Junior to Senior Divisions in non-STEM. Further separating participants by each STEM field produces large gender differentials within STEM (Figure 3, Panel C). Technology, engineering, and mathematics are dominated by male participants, and the gender differentials become larger from Junior to Senior Divisions. For example, the largest gender differentials are in the technology fields with 55 and 57 percentage point gaps in the Junior and Senior Divisions, respectively. Science fields have more female than male participants, however, the magnitude of gender gaps is smaller than the gender gaps in other STEM fields that favor males.

Table 2 shows the regression results for all participants, while Tables 3 and 4 separate by division. Each table displays the results with and without the county and year dummies. Table 2 includes all outcome variables. Outcome variables using non-STEM as the comparison group are found in Table 3, while within STEM results, which use science as the comparison group, are found in Table 4. Finally, Tables 3 and 4, Column 5 display the absolute value of t-statistics, testing the hypothesis that $\beta_{Junior} = \beta_{Senior}$.

Overall, females are about 5 percentage points less likely to enter the CSSF with a STEM project, compared to non-STEM (Table 2). Although significant, this result is not representative of the gender differentials when considering STEM subgroups. For example, females are 40 percentage points less likely to enter with technology projects. Engineering and math fields yield results smaller in magnitude, at 26 and 33 percentage points less likely in the overall samples, respectively. Outcomes variables exploring within STEM gender gaps yield significant results as well, but are smaller in magnitude compared to results in Columns 1 and 2. Introducing county and year dummies yields estimates that are similar in both magnitude and significance. Differences across California counties, for example, do not account for gender gaps. Additionally, the inclusion of control variables results in both slight increases and decreases in the coefficients.

In terms of change across age, gender gaps increase in magnitude across all specifications in Table 3. The outcome variable comparing technology and non-STEM fields yields the largest estimates with 36 and 42 percentage points for Junior and Senior Division participants, respectively. However, changes across age are only significant when comparing engineering or mathematics with non-STEM. Middle school females are 22 percentage points less likely to enter with engineering projects, increasing to 30 percentage points among high school students. Similarly, females are 26 percentage points less likely to enter in mathematics in middle school, increasing to 37 percentage points in high school.

Table 4 shows within STEM variation and the results largely follow from the previous findings. Females are significantly less likely to compete in technology, engineering, or mathematics fields, compared to science. Similar to the results in Table 2 and 3, introducing control variables results in nearly identical estimates. However, unlike the results in Table 3 that compare STEM with Non-STEM, within STEM gender gaps remain roughly stable across age. The largest and only significant change occurs when considering mathematics fields. Middle school females are 5.4 percentage points less likely to compete in mathematics, increasing to 8.6 percentage points in high school.

To summarize, large gender gaps in technology, engineering, and mathematics fields are present for all ages, and generally increase in magnitude from middle school to high school.

2.6 DISCUSSION

The remaining sections add context and assist with interpretation. I first compare the CSSF gender gaps to classroom enrollment outcomes. I then discuss the relevance of CSSF gender gaps today and how to interpret the results in the context of changing samples. Finally, I address the sample selection concerns that may be introduced due to the qualification process.

2.6.1 How Do Science Fair Gender Gaps Compare to Other Measures?

The previous analysis shows persuasive evidence that gender gaps exist across and within STEM. One of the benefits of studying science fair projects is the ability to explore specific subjects. By doing so, I am able to compare gender gaps to other gender gap measures. Among the current measures, course enrollment is the closest comparison group in that there are multiple options for students to choose from. Table 5 presents the percent of females in each subject using CSSF categories and classroom enrollment by age group.

Two features are clear immediately. First, the ability to draw comparisons is limited to five subjects and seven subject-age groups. The CSSF lacks specific math fields, like geometry, calculus, or algebra. However, the CSSF data presents information for 19 other subjects, which are not available in the class data. Second, the class enrollment statistics, even in advanced courses, show approximately equal representation of females and males, supporting the argument that students have limited flexibility in choosing classes in the presence of state graduation requirements or the argument that students enroll in technical courses to appeal to college admission boards.

Among the comparable groups, there are some similarities, as well as, notable differences. Chemistry and science subjects are similar in that they are generally gender balanced in both datasets. However, the general math field shows large gender differences in the CSSF with percent female in the low 30s. Differences also emerge in physics and biology, with about a 10 percentage point difference between the two sources of data. The California enrollment data shows near balanced composition, while the CSSF data shows an overrepresentation of females in biology, and an underrepresentation in physics.

To assess which measure is more informative for policy, I would ideally obtain information about CSSF participants' course enrollment. Further, I would follow these students to determine their future college degrees. In the absence of that information, I refer to bachelor degree statistics from the National Science Foundation, Division of Science Resources Statistics (2009), which states that 20 percent of physics and 58 percent of biology degrees are awarded to women. The CSSF data shows more gradual increases in gender disparities, starting in middle school, that are better aligned with college degree statistics.

2.6.2 Have Science Fair Gender Gaps Changed Over Time?

The 25 year time period studied in this paper may mask underlying trends. For example, any gender gaps observed with the pooled data may be driven by results in the earlier time period producing misleading conclusions. Further, even if I find that gender gaps are constant over time, with limited information about individuals, I cannot directly assess the impact of changing participant cohorts.

I explore gender gaps over time by estimating β by five five-year intervals. I test the null hypothesis that β_t is equal to β_{t-1}. Additionally, I interact $Gender_i$ with $Year$ and test for a non-zero time-trend. Tables 6 and 7 shows β by five-year intervals, while Table 8 presents the time-trend analysis. Both methods produce similar results in that there do not appear to be any general trends in the data. With one exception, none of the gender gaps are statistically different than the gender gap in the previous five-year period (not displayed). The exception is for the outcome variable engineering, relative to non-STEM, from 1990-1994 to 1995-1999. Further, the time-trend interaction coefficient is insignificant for all outcome variables, except STEM vs. Non-STEM. However, the magnitude is small at 0.001 percentage points.

There are a few ways to interpret these results because the composition of students changes over time. However, although the sample of students changes, the standards that they must meet do not. CSSF's strict quality standards ensure that students represent the best science fair projects in the state and are thus comparable across years.

Another argument could be that females who participate in the fair gain exposure to other types of projects and this exposure influences their interests, inspiring them to pursue topics that are traditionally male-dominated. Thus, the lack of change in these data does not indicate a lack of change in interests among participants. Although the vast majority of students only appear in the data once, 1,982 participate multiple years, allowing me to explore the validity of this concern. Out of the 1,982 students, 75 percent participate twice and 80 percent of those students compete with a one year gap. Among repeat students, approximately 50 percent are female and display similar gender gaps to the overall sample of CSSF students (both in their first and last years of participation). In terms of changing project fields, 70 percent of repeat participants remain in the field they compete in initially. Also, females are significantly less likely to switch (0.06 percentage points – not displayed). Among the 280 females who do switch fields, only 15 percent leave non-STEM for STEM, however, 86 percent of those moves are to science. Along similar lines, 88 percent of females who start in technology and end in a different field, end in science.

These results should be taken with caution. The students who repeat are not necessarily representative of overall participants. The similarities in gender differentials mitigate this concern, however, one could argue that repeat students are most committed to their fields of interests. With that said, among the students who do switch, the direction of movement is toward the least male-dominated STEM field. The direction of movement does not support the claim that the lack of change over time is uninformative.

2.6.3 Are State-Level Science Fair Gender Gaps Biased by Selection?

Finally, to mitigate the concern that the qualification process creates CSSF gender gaps, I explore gender differentials among county participants and winners. I then discuss if students dropping out between county and state bias CSSF gaps.

I construct and reference a dataset of individual-specific outcomes for county-level science fairs. I gather information from a variety of publicly available sources, including news press releases, fair programs, and award certificate booklets. Counties include Alameda, Los Angeles, San Diego, San Francisco, Santa Barbara, and Santa Clara. I choose counties that are located throughout California, host large fairs, and send the most students to the CSSF.

I employ the above methodology using SSA data to identify gender with one change in determining student age. Los Angeles, San Francisco, Santa Barbara, and Santa Clara do not report grade. I match names based on average age by division. Appendix Table 2 lists the counties, years, and available level of information. There are 3,843 individuals, with the majority representing county fair winners. The lack of participant data is not of great concern because the majority of students at county fairs receive an award and thus, show up in my data. For example, the two counties that make participant information available, Alameda and Santa Barbara, award 71 and 60 percent of their participants receives an award. Thus, it is not unreasonable to assume that award winners are representative of overall participants, by gender.

County fairs, likely due to small samples, generally combine the computer, technology, and math fields. I label these fields as "math-and-tech" and create the same variable using the CSSF sample to draw comparisons. Table 9 shows the percentage of females in each STEM field by division at the county and state levels.

I find similar patterns in female participation at both science fair levels. The largest difference is among Senior Division participants in the math-and-tech field. At the CSSF, 27 percent of participants are female, while at the county level 42 percent are female. Although still consistent with claim that females are underrepresented in these fields, this discrepancy may indicate that selection drives some of the CSSF results. However, the gender gaps for the other STEM fields do not show similar patterns. Further, replicating the regression estimates using the county data shows that the estimates are generally larger in magnitude than those in the CSSF (not displayed).

In terms of who drops out from county to state, I cannot rule this out as a source of bias. However, if relevant, this bias is minimal and does not challenge the overall findings of the paper. For example, in 2010, only 9 Junior Division and 13 Senior Division students did not show up to the CSSF. Nine of those students are female and 11 are male (gender for the remaining two is unknown). Similar patterns exist in other years, but future work is necessary to substantiate this claim. The results described in this section suggest that selection through the qualification process does not bias CSSF gender gaps.

2.7 CONCLUSION

I propose using science fair projects as an alternative measure of the STEM gender gap. Using a student's choice of project, which places him or her in a STEM field, I evaluate the age of gender gap emergence and change across age. The data show balanced gender composition among all CSSF participants, however, large gender differentials are present among middle school students that become more distinct in high school when looking at technology, engineering, and mathematics. I further explore gender gaps among specific fields and compare the findings to classroom enrollment results. Gender gaps do not appear in the classroom data, but are prominent in the CSSF category data. Finally, I show that gender gaps are constant over time and the CSSF qualification process does not bias the central findings. In terms of implications, this paper's findings suggest that to prevent females from dropping out of the STEM pipeline, efforts to reduce the gap must occur in middle school and beyond. More importantly, gender gaps in middle school are large in magnitude, especially compared to conventional measures, suggesting that targeting students in elementary school is critical to the reduction of the gender gap.

Table 2.1: Science Fair Sample Composition

	Junior Division	Senior Division
STEM	91%	92%
Science	63%	65%
Technology	5%	5%
Engineering	19%	14%
Math	4%	8%
N Participants	11,133	6,132

Table 2.2: State Science Fair Gender Gap Regression Results

Dep Var	*STEM vs Non-STEM*		*Science vs Non-STEM*	
Gender	-0.052***	-0.053***	-0.042***	-0.044***
	(0.004)	(0.004)	(0.006)	(0.006)
County		x		x
Year		x		x
N	17265	17265	12463	12463
Dep Var	*Technology vs Non-STEM*		*Technology vs Science*	
Gender	-0.400***	-0.382***	-0.085***	-0.084***
	(0.018)	(0.018)	(0.005)	(0.005)
County		x		x
Year		x		x
N	2250	2250	11831	11831
Dep Var	*Engineering vs Non-STEM*		*Engineering vs Science*	
Gender	-0.255***	-0.250***	-0.129***	-0.127***
	(0.013)	(0.013)	(0.007)	(0.007)
County		x		x
Year		x		x
N	4509	4509	14090	14090
Dep Var	*Math vs Non-STEM*		*Math vs Science*	
Gender	-0.326***	-0.312***	-0.069***	-0.066***
	(0.019)	(0.019)	(0.005)	(0.005)
County		x		x
Year		x		x
N	2366	2366	11947	11947

Notes: * p<0.05, ** p<0.01, *** p<0.001. Gender is a dummy variable that equals one if the participant is female.

Table 2.3: State Science Fair Gender Gap Regression Results, by Division

	Junior Division	Senior Division	Junior Division	Senior Division	T-Statistic
	(1)	(2)	(3)	(4)	(5)
Dep Var: STEM vs Non-STEM					
Gender	-0.046***	-0.062***	-0.048***	-0.062***	1.538
	(0.005)	(0.007)	(0.005)	(0.007)	
County & Year Dummies			x	x	
N	11133	6132	11133	6132	
Dep Var: Science vs Non-STEM					
Gender	-0.033***	-0.058***	-0.037***	-0.059***	1.699
	(0.007)	(0.009)	(0.007)	(0.009)	
County & Year Dummies			x	x	
N	7996	4467	7996	4467	
Dep Var: Technology vs Non-STEM					
Gender	-0.380***	-0.439***	-0.355***	-0.417***	1.546
	(0.023)	(0.031)	(0.023)	(0.032)	
County & Year Dummies			x	x	
N	1459	791	1459	791	
Dep Var: Engineering vs Non-STEM					
Gender	-0.232***	-0.304***	-0.224***	-0.304***	**2.449**
	(0.016)	(0.024)	(0.016)	(0.024)	
County & Year Dummies			x	x	
N	3124	1385	3124	1385	
Dep Var: Math vs Non-STEM					
Gender	-0.274***	-0.390***	-0.264***	-0.374***	**2.816**
	(0.024)	(0.030)	(0.024)	(0.030)	
County & Year Dummies			x	x	
N	1419	947	1419	947	

Notes: * p<0.05, ** p<0.01, *** p<0.001. Gender is a dummy variable that equals one if the participant is female. T-statistic estimates measure the difference between Junior and Senior Division coefficients, including county and year dummies.

Table 2.4: Gender Gaps by Division, within STEM

	Junior Division	Senior Division	Junior Division	Senior Division	T-Statistic
	(1)	(2)	(3)	(4)	(5)
Dep Var: Technology vs Science					
Gender	-0.086***	-0.084***	-0.085***	-0.083***	0.18
	(0.006)	(0.008)	(0.006)	(0.008)	
County & Year Dummies			x	x	
N	7545	4286	7545	4286	
Dep Var: Engineering vs Science					
Gender	-0.139***	-0.112***	-0.137***	-0.111***	1.92
	(0.009)	(0.011)	(0.009)	(0.011)	
County & Year Dummies			x	x	
N	9210	4880	9210	4880	
Dep Var: Math vs Science					
Gender	-0.054***	-0.091***	-0.052***	-0.087***	**3.575**
	(0.006)	(0.009)	(0.006)	(0.009)	
County & Year Dummies			x	x	
N	7505	4442	7505	4442	

Notes: See Table 2.3 notes.

Table 2.5: Category and Classroom Enrollment Gender Gaps, Percent Female

General Subjects*	CA Middle School	CA High School	CSSF Middle School	CSSF High School
Science (AP Science)	50	(51)	56	54
Technology			22	22
Engineering			39	36
Math (AP Math)	50	(52)	33	30
Specific Subjects				
Aerodynamics / Hydrodynamics			28	27
Algebra I	50			
Algebra II		52		
Alternative Energy & Power			41	
Applied Mechanics & Structures / Manuf.			34	32
Behavioral & Social Sciences			64	69
Biochemistry / Molecular Biology			57	50
Biology		49	59	56
Botany			61	
Calculus		49		
Chemistry		52	50	50
Cognitive Science			67	
Earth & Planetary Sciences / Physical Env.			50	49
Electronics & Electromagnetics			22	23
Engineering			32	27
Environmental Engineering			52	51
Environmental Science			56	60
Geometry		50		
Mammalian Biology			61	58
Materials Science			51	
Microbiology			63	61
Pharmacology / Toxicology			62	60
Physical & Biological Product Science			56	
Physics		48	46	38
Physiology			60	58
Plant Biology			57	59
Zoology			60	60

Notes: Data about California students are from the 2009 Civil Rights Data Collection. CSSF category gender composition values are displayed if the number of students exceeds 100. *CSSF values for Biology are weighted averages of all biology categories.

Table 2.6: Gender Gaps by Five-Year Period

Years:	1990-94	1995-99	2000-04	2005-09	2010-14
Dep Var: STEM vs Non-STEM					
Gender	-0.059***	-0.059***	-0.060***	-0.049***	-0.036***
	(0.011)	(0.011)	(0.010)	(0.008)	(0.008)
N	2892	3307	3365	3873	3828
Dep Var: Science vs Non-STEM					
Gender	-0.047**	-0.049**	-0.049***	-0.043***	-0.030**
	(0.014)	(0.015)	(0.014)	(0.011)	(0.010)
N	2153	2294	2403	2832	2781
Dep Var: Technology vs Non-STEM					
Gender	-0.422***	-0.296***	-0.332***	-0.480***	-0.397***
	(0.043)	(0.040)	(0.041)	(0.040)	(0.046)
N	368	471	482	500	429
Dep Var: Engineering vs Non-STEM					
Gender	-0.261***	-0.212***	-0.274***	-0.281***	-0.218***
	(0.033)	(0.029)	(0.030)	(0.030)	(0.029)
N	773	1019	963	879	875
Dep Var: Math vs Non-STEM					
Gender	-0.358***	-0.283***	-0.285***	-0.346***	-0.342***
	(0.045)	(0.040)	(0.042)	(0.043)	(0.047)
N	405	540	525	469	427

Notes: See Table 2.2 notes. All regressions also include county and year dummies.

Table 2.7: Gender Gaps by Five-Year Period, within STEM

Years:	1990-94	1995-99	2000-04	2005-09	2010-14
Dep Var: Technology vs Science					
Gender	-0.079***	-0.070***	-0.068***	-0.111***	-0.087***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
N	1983	2087	2213	2794	2754
Dep Var: Engineering vs Science					
Gender	-0.127***	-0.112***	-0.146***	-0.135***	-0.122***
	(0.017)	(0.017)	(0.016)	(0.014)	(0.014)
N	2388	2635	2694	3173	3200
Dep Var: Math vs Science					
Gender	-0.066***	-0.071***	-0.066***	-0.057***	-0.072***
	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)
N	2020	2156	2256	2763	2752

Notes: See Table 2.2 notes. All regressions also include county and year dummies.

Table 2.8: Gender Gaps Linear Time Trend Results

Dep. Var.	*STEM vs. Non-STEM*	*Science vs. Non-STEM*	*Technology vs. Non-STEM*	*Engineering. vs. Non-STEM*	*Math vs. Non-STEM*
Gender * Year	0.00*	0	0	0	0
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gender	-3.05**	-2.67	4.39	-1.59	1.67
	(1.18)	(1.61)	(5.27)	(3.83)	(5.47)
Year	0.00***	0.00***	0.01***	0.00**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-2.20**	-4.20***	-23.19***	-6.64*	-12.15**
	(0.84)	(1.22)	(3.73)	(2.62)	(3.98)
N	17265	12463	2250	4509	2366

Dep. Var.	*Technology vs. Sci*	*Engineering. vs. Sci*	*Math vs. Sci*
Gender * Year	0	0	0
	(0.00)	(0.00)	(0.00)
Gender	2.02	0.53	-0.09
	(1.29)	(1.94)	(1.37)
Year	0.00***	-0.00*	0
	(0.00)	(0.00)	(0.00)
Constant	-3.57***	3.21*	1.32
	(0.95)	(1.40)	(1.01)
N	11831	14090	11947

Notes: See Table 2.2 notes. All regressions also include county and year dummies.

Table 2.9: State and County Gender Gaps by Division, Percent Female

	CSSF	County	CSSF	County
	Junior Division		Senior Division	
Science	56%	52%	54%	58%
Engineering	37%	31%	35%	35%
Math-and-Tech	28%	34%	29%	42%
Social Science	64%	63%	68%	69%

Figure 2.1: Number of Junior and Senior Division Participants Over Time

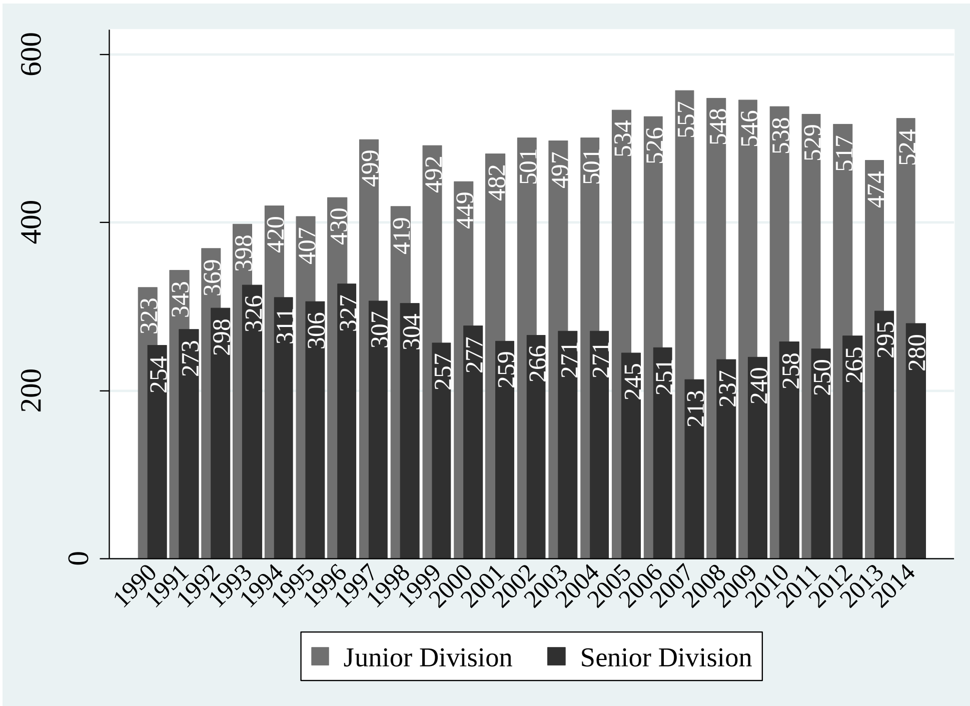
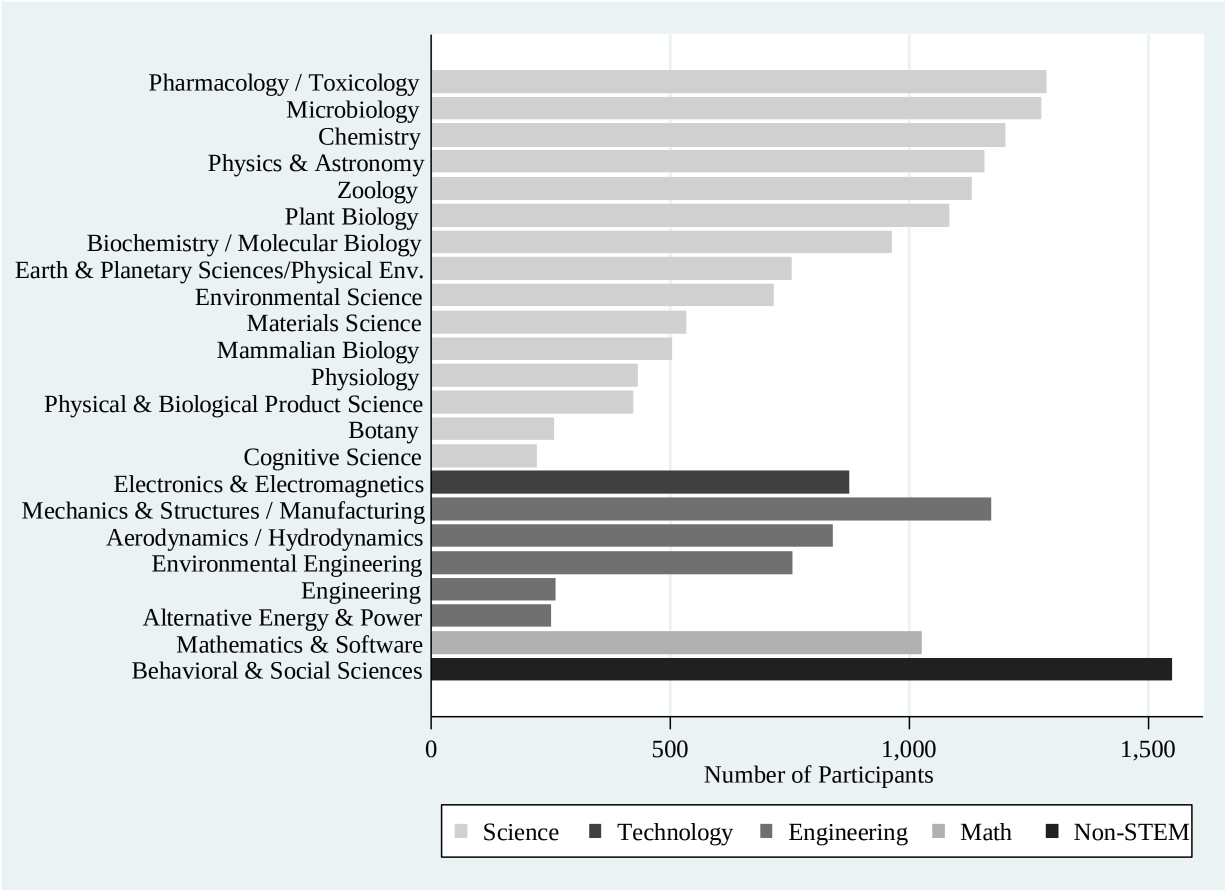
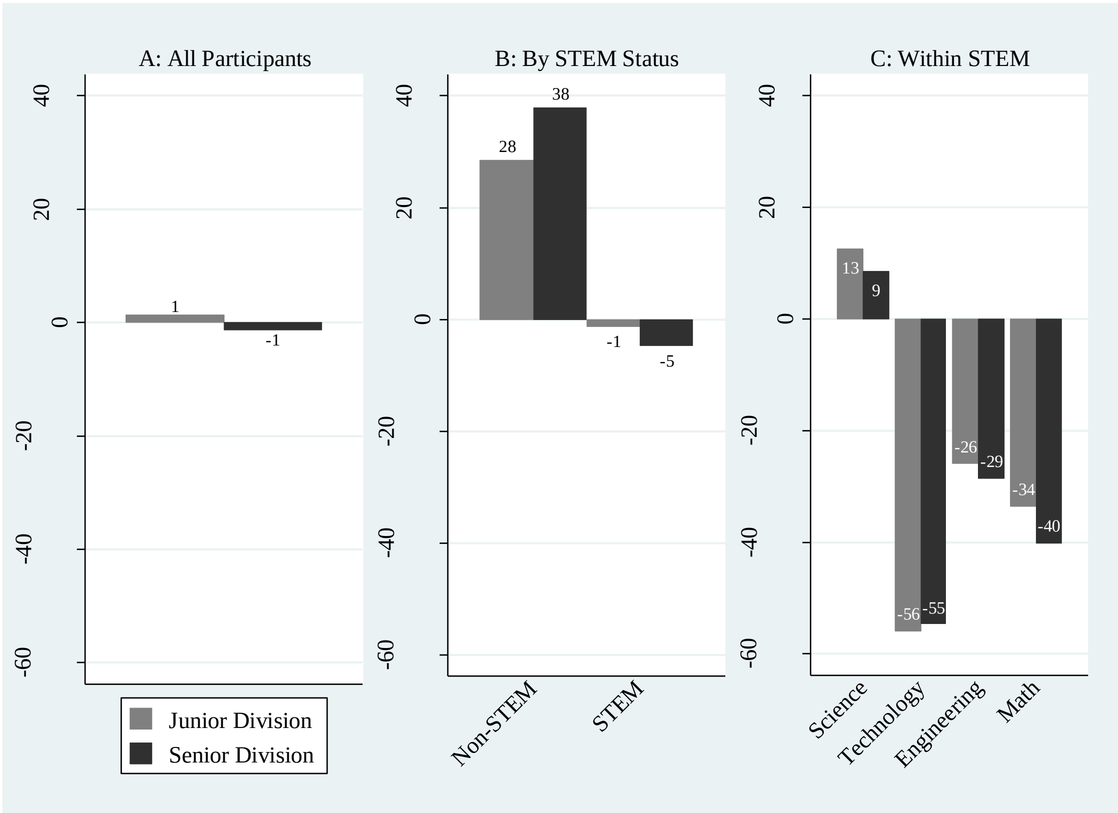


Figure 2.2: Number of Participants by Category and STEM Field



Notes: Category titles are on the y-axis and colors indicate the associated STEM field. The y-axis is first sorted by STEM field, then by category popularity.

Figure 3: Gender Gaps by Division, Percentage Point Differences



Notes: A value of zero indicates balanced gender composition. Negative values indicate an underrepresentation of females and bar heights correspond to the percentage point difference in female and male participation.

CHAPTER 3

Fertility Assimilation: The Role of Culture

3.1 INTRODUCTION

The elimination of the United States' National Origin Quota System in the 1965 Hart Cellar Act spurred large-scale immigration from non-European countries. The rapid influx of immigrants greatly impacted local labor markets and institutions, inspiring a large body of research on immigrant assimilation.[35] In particular, many studies examined fertility assimilation,[36] defined as the convergence between immigrant and native fertility levels across generations, as an indicator of immigrant well-being. The fertility assimilation model from the sociology literature predicts that as women assimilate in other aspects, their fertility levels change to meet native fertility levels (Goldstein and Goldstein, 1983; Kahn, 1988; Ford, 1990; Lucas, 1994).[37] On the other hand, economic fertility theory models a couple's demand for children as a function of female (potential) wages, male income, and the price of fertility regulation. It predicts that the demand for children decreases as the opportunity cost of the mother's time increases.[38] However, I show that socioeconomic factors poorly explain fertility assimilation for certain immigrant groups. Instead, I suggest an alternative explanation for fertility assimilation: convergence in

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[35] For example, assimilation studies have analyze labor market outcomes like earnings and unemployment (Schmidt, 1995; Bauer and Zimmermann, 1997; Schoeni, 1998; Chiswick et al., 1997), and transfer program participation. (Baker and Benjamin, 1995; Hu, 1998; Borjas and Hilton, 1996; Riphahn, 1998).

[36] Researchers also study the potentially disruptive effect of migrating on fertility decisions. I account for the influence of migration in the data section.

[37] The demographic literature has neglected the economic rationales for couples changing their childbearing behavior over and within generations (Mayer and Riphahn, 1999).

[38] Becker (1981) models a couple's demand for children as a function of prices and income. The effect of husband's income is ambiguous. The supply side determinants of fertility include the price of fertility regulation (Easterlin, 1987; Rosenzweig and Schultz, 1985).

culturally driven child-sex composition preferences. Intuitively, as immigrants adopt the native preference for mixed-sex children, their childbearing behavior will mimic those of natives and fertility assimilation will occur.[39]

To show that fertility assimilation may be linked to child-sex composition preferences, I study women from China, India, or South Korea because they make up the largest group of immigrants from countries in which son preference is a well-documented phenomenon.[40] [41] I first evaluate if the preference for sons is sustained after migration. I then determine child-sex composition preferences for second-generation women. Finally, the primary contribution of this paper, I explore if evolving preferences across immigrant generations impact fertility assimilation results.

To determine preferences, I evaluate the probability of having an additional child, conditional on the sex of the previous birth(s), and explore male to female sex ratios at birth.[42] I find that first-generation women from China, India, or South Korea are significantly more likely to have a third child if the first two are females. Additionally, the male to female sex ratio at birth for the third child among first-generation households is above normal levels if the previous two children are daughters.[43] Second-generation

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[39] Economists have recently brought attention to the significant role of culture in immigrant socioeconomic outcomes, including fertility (Fernandez and Fogli, 2006, 2009, 2010; Moehling and O'Grada, 2006).

[40] As Clark (2000) describes, "the term son preference refers to the attitude that sons are more important and more valuable than daughters" (p. 95). There is a large body of work documenting the presence of son preference in China (Arnold and Zhaoxiang, 1987; Hull, 1990; Tuljapurkar, Li, and Feldman, 1995), India (Das, 1987; Clark, 2000), and Korea (Arnold, 1985; Park and Cho, 1995).

[41] Chapter 3, Appendix 1 discusses immigration rates.

[42] From a behavioral standpoint, child-sex composition preferences may manifest in two ways. First, mothers may continue to have children until the desired outcome is achieved. Second, women may engage in sex-selective procedures, resulting in skewed male to female sex ratios at birth. Currently, parents in the U.S. can select the sex of their children through abortion, in vitro fertilization (IVF), or sperm sorting, which is often used in conjunction with IVF.

[43] Chahnazarian (1988) finds a biologically normal range of 103-108 boys per 100 girls.

Chinese, Indian, and South Korean women do not exhibit a bias toward sons, and instead their fertility behavior, similar to that of native women, is indicative of a preference for mixed sibling-sex composition.[44]

In the presence of child-sex composition preferences, assimilation results will differ depending on whether or not the households achieve their ideal outcomes. If a son is achieved at earlier parities, then immigrant women will have less children than natives, yielding large immigrant and native fertility differentials. However, if immigrant women do not achieve a son quickly, then they will continue to have more children, which would result in higher fertility levels, closing the gap between them and natives. The standard method to evaluate fertility assimilation, regressing number of children on an immigrant or native indicator, would not reflect differences in household composition subsamples, which, all else equal, are reflections of child-sex composition preferences. Thus, I present the assimilation results disaggregated by household composition. I condition on whether or not households achieved the ideal child-sex composition in the first two births. For example, I compare first-generation immigrant households that achieved at least one son to native households with mixed-sex children.

Without disaggregating households by composition, there appears to be a small, but significant decline in the fertility gap across generations. However, among households that achieve their preferred child-sex composition outcomes there is a substantial decline in the fertility differential across generations. Conversely, households that did not achieve their

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[44] Angrist and Evans (2002) find that native women prefer mixed sibling-sex composition. Almond, Edlund, and Milligan (2013) examine sex ratios for Chinese, Indian, Korean, and Vietnamese immigrants in Canada to determine how they vary from the high male to female ratios in their home countries. They find that sex ratios are high among first-generation immigrants if the previous births are female. Second generation immigrants have sex ratios closer to normal levels.

ideal child-sex composition outcome show insignificant assimilation results. The initial significant finding indicating that fertility assimilation occurs is driven by households that achieve their ideal outcomes. Among those households, however, the assimilation result is driven by the fact that first-generation women are relatively more likely to stop having children when they have a son. No such behavior is present for second-generation women because they have adopted the native preference for mixed-sex children.

The final portion of the paper shows that these paper's findings are robust to including several control variables, including education which is often a significant driver of fertility assimilation. I also attempt to explain why preferences change across immigrant generations. I discuss possible socioeconomic mechanisms using Bisin and Verdier's (2000, 2001) model of cultural trait transmission, supplementing their theoretical model with empirical evidence from the economics literature.

3.2 LITERATURE REVIEW

Fertility assimilation studies focus on several overarching themes. First, researchers are concerned with correctly setting up the data. This includes addressing the potential differences between estimates based on cross-sectional data and data that align synthetic immigrant cohorts.[45] Cross-sectional comparisons of first, second, and third generation Hispanic immigrants do not find a convergence in fertility toward native levels (Bean, Swicegood, and Berg 2000; Frank and Heuveline 2005; Swicegood and Morgan 1999). However, Parrado and Morgan (2008) reexamine Hispanic and Mexican fertility while implementing a 25 year lag to compare different generations. They combine data from

[45] Cross-sectional studies of immigrant assimilation compare different generations within the same survey year. In contrast, studies that create synthetic immigrant cohorts use multiple cross-sections.

multiple U.S. censuses and the CPS and find evidence in support of convergence in fertility levels between Hispanic and native women across immigrant generations. They emphasize that the increase in the fertility gap found in the previous research is a result of misaligned cross-sectional data.

The studies listed in the previous paragraph use multiple years to describe the first-generation cohort, raising a second data concern. Kahn (1994) notes that using different census years to describe the first-generation may reflect unobservable traits attributed to selection from the source country. She does not discuss how changing source country characteristics may affect fertility outcomes in the U.S. For example, Stephen and Bean (1992) use 1970 and 1980 census data and find evidence in favor of assimilation in fertility levels. During this time period, however, Mexico's total fertility rates are declining. First-generation immigrants present in the 1980 sample may have lower fertility outcomes due to the changing norms in Mexico, and not necessarily due to assimilation to U.S. norms.

Once fertility differentials are determined, researchers often attempt to identify why immigrants and natives differ in childbearing behavior, which generally involves controlling for variables, like age and educational attainment. Country of birth or ancestry variables are also included to account for cultural differences across immigrant groups, however, these variables do not account for any within country differences. Also, fertility behavior driven by culture is often conditional on the sex of the previous child or children which is also not accounted for in these studies. For example, Kahn (1994) attempts to identify the source of the fertility gap between first-generation immigrants and natives during the 1980s. She uses 1980 census data as well as the 1986 and 1988 June CPS to obtain information for expected future childbearing behavior. After controlling for income, age, education, and ethnicity, she finds that immigrants have lower fertility than natives. Missing in her paper and in other fertility assimilation studies are control variables for the sex of the children.

The second set of studies relevant to this paper discuss the presence of son preference among Chinese, Indian, and South Korean households. International concern for imbalanced male to female sex ratios grew after Amartya Sen's (1990) pioneering essay coined the term "missing women." Since then, many have described the imbalanced sex ratios in the source countries and note that introducing sex-selective technology bans do not mitigate the problem (Chung and Das Gupta, 2007; Almond and Edlund, 2008; Hesketh, et. al, 2009).[46]

Almond, Edlund, and Milligan (2013) examine sex ratios and childbearing behavior of Chinese, Indian, Korean, and Vietnamese immigrants in Canada. They find that sex ratios are high among first-generation immigrants if the previous births are female and that first-generation women will continue to have children until a son is achieved. Second-generation immigrants have sex ratios closer to normal levels. Although they do not discuss the reasons why preferences may change across generations, they note that "assimilation of values would raise the psychic cost of sex selection" and reduce imbalanced male to female sex ratios. The purpose of their paper is to determine if son preference is maintained in Canada, which it is. This paper does the same for immigrants in the U.S., but with the purpose of using changes in preferences across generations as a possible source of fertility assimilation.

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[46] Sex selection abortion bans in China (1994), India (1994), and South Korea (1987-ban on revealing sex) have received international support.

3.3 DATA & DESCRIPTIVE STATISTICS

Information would ideally come from a panel dataset that tracks fertility behavior before and after migration until childbearing is complete. To evaluate assimilation, the data would include fertility outcomes for the children of these immigrants. Additional information would be necessary to account for potentially disruptive effects of migration itself or immigrant self-selection.[47] For example, explicitly asking women questions about the number of desired children prior to migration would give some indication to how migration alters fertility plans.[48] No such dataset exists and researchers introduce various solutions to overcome data limitations. I describe these methods below and outline additional improvements that I implement in constructing some of the variables and setting up the data.

I define first-generation Chinese, Indian, or Korean immigrants as foreign born individuals residing in the U.S. Due to limitations in the data, second-generation immigrants are individuals born in the U.S. who identify their ancestry as Chinese, Indian, or Korean. Ideally, I would identify second-generation immigrants as women whose parents were born abroad, but parent birthplace is not available in this dataset. For simplicity, I refer to all women who claim Chinese, Indian, or Korean ancestry as second-generation immigrants, even though they may be third generation or beyond. Given the

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[47] The disruption hypothesis involves factors associated with the move itself that may lower fertility. These factors include the effects of spousal separation (Goldstein, Goldstein and Piampiti, 1973) or stress due to the migration (Hervitz, 1985). The disruptive effect on fertility is often described as temporary and inconclusive in terms of the effect on household size in the long run. Fertility may decline immediately after the move, but resume its previous level or even accelerate to compensate for the disruption (Goldstein and Goldstein, 1973; Stephen and Bean, 1992; Moss, Stone et. al, 1993).

[48] Socioeconomic characteristics after migration, although available in U.S. datasets, are inadequate in determining if and how selection occurs. Often researchers look at descriptive statistics for immigrants and compare them to home country statistics to draw conclusions about selection.

migration rates discussed in Appendix 2, I do not think interpreting this group as second-generation immigrants is problematic.

To properly align the first and second generations, I use data from the 1990 Census and the 2006 through 2012 American Community Surveys. I choose 1990 to describe first-generation women because it captures a large sample, while still allowing for an appropriate second generation comparison.[49] For example, if I use 2000 data for the first-generation, the sample would be larger, but the corresponding second-generation would not be in the data yet.

I determine the 16 to 22 year lag based on mother's average age at first birth and the first child's average age.[50] First-generation women in 1990 are on average 36 years old and had their first child about 8 years earlier at age 28 (Table 1). In 1990, the majority of the second-generation is between 2 and 14 years old. I find that second-generation women are about 29 years old when they have their first child. Thus, using 1990 data for first-generation immigrants means that the corresponding second-generation start having children in 2011, on average. To increase the sample size for second-generation women, I expand the years to include 2006 through 2012.[51]

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[49] These comparisons control for the selectivity of entry cohorts because the entry cohort is held constant (Kahn, 1994).

[50] None of the assimilation studies listed throughout this paper justify how the lag is determined. They range between 10 and 25 years.

[51] One potential issue for using more recent data for the second-generation is that their fertility may not be completed. For this particular immigrant group, this does not pose a serious problem. Second-generation women above the age of 44 in 1990 have an average of 1.73 children and 1.68 children in the 2006 to 2012 sample. For households with at least two children, women are younger when they have their first child and there is about a 2 year age difference between the first and second child. For example, second-generation women who ultimately had at least 3 children were 26 when they started having children, making the 2006 to 2012 range more reasonable.

In the next section, I evaluate fertility behavior conditional on the sex of the first born or the sex of the first two children, requiring that all women in the sample have at least one child. I match mothers to children within households to capture the sex, birthplace, and age of the first three children. I impose the age restriction that mothers are between 16 and 50 years old, making the average age for the oldest child 12 years old.[52]

I also require that all children are born in the U.S. This restriction accounts for the possibly disruptive effects of migration and ensures that fertility decisions are made in an environment where mixed sibling-sex composition is preferred (Almond, Edlund and Milligan, 2013).19 Approximately 32 percent of the first-generation had their first child born outside of the U.S., and about 20 percent had the first two births abroad. I do not claim that this is the ideal solution to avoiding the possibly disruptive effects of migration. It could be the case that a woman may have decided to delay childbirth if she knew she would migrate in the near future. Changes in fertility behavior would be driven by migration and not necessarily adjustment to host country norms. However, conclusions about assimilation are not affected if the disruptive effects are temporary because they draw from total number of children. On the other hand, if the migration process causes a permanent change in childbearing behavior, the assimilation conclusions are influenced. Others have found that it is less likely that migration causes a permanent change in fertility behavior if the woman migrated at a younger age (Ford, 1984, 1990; Hervitz, 1985). My conclusions below are robust to restricting the sample to younger women (not displayed).

[52] The dataset includes information for all individuals within a household, and does not track children across households.

Table 1 provides descriptive statistics for natives, first-generation and second-generation immigrants from China, India, or South Korea. Demographic and socioeconomic variables include mother's age, age at first birth, education, marital status, employment status, hours worked, and income variables. Weekly hours worked and wage and salary income variables are conditional on employment. Several of these variables are used to discuss the mechanisms that drive changes in fertility behavior in Section 5.

About 60 percent of first-generation immigrants are employed. This number increases to about 70 percent in the following generation, which is nearly equivalent to native levels. Both first and second-generation Chinese, Indian, or South Korean women have higher wages relative to native women. Second-generation women work slightly less hours compared to the first-generation, but earn about two times more in wage and salary income, conditional on employment. Family income increases across natives and immigrants, but immigrant households see a much larger relative increase. In 1990, first-generation household family income is approximately $25,000 more than native households. This difference increases to $60,000 when comparing second-generation and native households.

Second-generation women have higher average years of education, but are less likely to be married compared to the first-generation. Intermarriage is also more common among second-generation women. About 60 percent of these women marry a man who does not share their cultural background, compared to 17 percent of the first-generation sample. Finally, about 65 percent of the second-generation sample obtains a bachelor's degree, exceeding natives and first-generation immigrants.

3.4 METHODOLOGY & RESULTS

I employ two methods to draw conclusions about child-sex composition preferences. First, I determine if women are more likely to have an additional child conditional on the sex of the previous child or children. Second, I look at male to female sex ratios at birth to determine if women engage in sex-selective behavior.[53] Once preferences are established, I introduce them in the assimilation framework, employing OLS regressions to determine the fertility differential between immigrants and natives. I disaggregate households by whether or not they achieve their preferred child-sex composition and explore differences in assimilation results. If preferences are correlated with childbearing behavior, then the behavior would differ by whether or not the preferred (or ideal) child-sex composition is achieved.

3.4.1 Child-Sex Composition Preferences

I employ the following regression to determine if women are more likely to have an additional child, conditional on the sex of the previous birth:

$$Y_i = \alpha_i + \beta_i I(SexComposition)_i^j + X_i'\delta + \varepsilon_i \tag{1}$$

The dependent variable Y_i is an indicator for whether a woman has an additional child. $I(SexComposition)_i^j$ ($j = 1,2,3$) represents three indicator variables for the sex composition of the child or children in the household. $I(SexComposition)_i^1$ equals one if the first born is female, $I(SexComposition)_i^2$ equals one if the first two children are female and zero if they are male, and $I(SexComposition)_i^3$ equals one if the first two children are mixed-sex. I run three sets of regressions, each with a different dummy variable.

[53] Due to the timing of introduction and associated costs, it is likely that the imbalanced sex ratios are primarily driven by abortion and fertility stopping rules.

Regressions using $I(SexComposition)_i^1$ condition on households with at least one child, while regressions using the other two indicators condition on households with at least two children. A positive coefficient, β, means that a woman is more likely to have an additional child if $I(SexComposition)_i^j$ equals one.

X is a vector of control variables, including ancestry, mother's age, and father's age. Year fixed effects are included for the second-generation regressions. I incorporate education, employment status, intermarriage, and ethnic enclave residence individually in the following section. Also, although not displayed, the results are robust to controlling for mother's age at first birth and marital status.

Table 2a presents estimates for all first-generation and second-generation women, while Tables 2b and 2c separate women by country of birth or ancestry. Coefficients in Table 2a, Column 1 are insignificant across native, first-generation, and second-generation households, indicating that the sex of the first born is uncorrelated with the decision to have more children. Among natives, the β coefficient is similar in magnitude across specifications. They are significantly more likely to have a third child if the first two children are the same sex.

I find greater variation in behavior among first-generation Chinese, Indian, or Korean women. They are nearly 11 percentage points more likely to have a third child if the first two children are female, relative to two males. Similarly, they are 13.2 percentage points more likely to have a third child if the first two children are female, relative to those with mixed-sex children, but are only 2.3 percentage points more likely to have a third child if the first two children are male.

Comparing Panels B and C from Table 2a yields interesting generational differences. Fertility behavior appears to be substantially different for second-generation women in that the desire to have a son is less influential and possibly no longer relevant. The coefficient of -.036 for second-generation women with two children of the same-sex and those with mixed-sex children is notable because it is not driven by the estimate in Column 5, which compares mixed-sex children with all female households. It appears that second-generation women from China, India, or South Korea exhibit a preference for mixed sibling-sex composition, similar to native women.

Table 2b looks at each first-generation immigrant group separately. The estimates in Columns 2 through 5 support the son preference hypothesis across the three groups.[54] The patterns among second-generation women are consistent when separating women by ancestry as well (Table 2c).

To further support the claim that first-generation households prefer sons and second-generation and native households prefer mixed sibling-sex composition, I look at male to female sex ratios at birth. As reported in Table 3, I find that sex ratios for the first child fall within the normal range (103 to 108 boys to 100 girls). Among first-generation women, sex ratios at birth suggest that they are more likely to give birth to a son when that have previously only given birth to girls.[55]

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[54] Appendix 2 replicates the estimates for first-generation immigrant women in the 2006 to 2012 data to ensure that the preference for sons is not a period effect. It appears that son preference is still present in the more recent data. The estimates are similar in magnitude and significance to those in the 1990 cohort.

[55] Evidence for son preference is also present in the sex ratios at birth for first-generation women in the 2006 to 2012 sample (Appendix 3). In addition to having skewed sex ratios for the third birth (conditional on previously having daughters), sex ratios for the second birth are relatively more skewed toward sons compared to the 1990 estimates. The male to female sex ratios for the third birth, conditional on having sons previously, are slightly below the normal minimum. However, this is likely due to small sample sizes. For example, there are 1,431 Korean women with a third child

Sex ratios for the first and second child are within the normal range for second-generation women. Interestingly, the male to female sex ratios for the third birth are heavily skewed. There are 1.32 males for every female if the first two born are girls. Unlike the first-generation, there is a reverse effect when conditioning on two sons. Households with two sons are disproportionately more likely to have a daughter as the third child. This implies that the third birth for second-generation women yields a child of the opposite sex if the first two were of the same sex, providing support for the mixed sibling-sex preference. To summarize, first-generation women behave as if they prefer sons, while second-generation women adopt U.S. norms and behave as if they prefer mixed-sex children.

3.4.2 Fertility Assimilation

The next portion of the analysis determines if the previously established child-sex composition preferences affect fertility assimilation conclusions. The immigrant group studied in this paper has lower fertility levels than the native population. Thus, assimilation occurs if immigrants across generations have more children relative to natives, reducing the fertility gap. I estimate the following model to find fertility differentials between immigrants and natives:

$$Y_i = \beta_0 + \beta_1 I(First\ Generation\ )_i + \ \beta_2 I(Second\ Generation\ )_i + X_i'\delta + \varepsilon_i \qquad (2)$$

where $I(First\ Generation\ )_i$ and $I(Second\ Generation\ )_i$ are indicators that equal one if the individual is an immigrant and zero if native, with reference to generation. The coefficients β_1 and β_2 estimate the immigrant and native fertility differentials. Differences

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and only 346 with two sons first. From Appendix 3, first-generation women with two daughters are significantly more likely to have a third child relative to women with two sons, which is consistent by country of origin.

between β_1 and β_2 capture changes in the fertility gap across generations. In order to evaluate $\gamma_1 = (\beta_1 - \beta_2)$, I use:

$$Y_i = \gamma_0 + \gamma_1 I(First\ Generation\ )_i + \gamma_2 I(First\ or\ Second\ Generation\ )_i + X_i' \partial + \omega_i \quad (3)$$

The dependent variable Y_i is number of children. All regressions control for country of ancestry, mother's age, and state and year fixed effects.[56] I interact with education, employment, intermarriage, or ethnic enclave residence variables in Table 5. Sample weights are also incorporated in the analysis.

Table 4 displays the fertility differentials for the overall sample and by household composition. Native women have more children than the immigrant group studied here. Comparing the first-native fertility gap with the second-native gap suggests the presence of assimilation, with the fertility gap declining by almost half. The estimates presented in Columns 2 and 3 incorporate child-sex composition. The first set of estimates in Column 2 condition on households that do not achieve the ideal sex composition: the first two children in first-generation immigrant households are female, while the sex of the first two children is the same in native or second-generation households.

I previously show that first-generation women are more responsive when they do not achieve the ideal child-sex composition. Thus, I expect there to be a "catch up" effect in that first-generation immigrant households will have more children and close the fertility gap. If this effect is large enough, then they may have households larger than natives, which would dramatically affect the assimilation conclusions.

The estimates in Table 4, Column 1 show that the fertility gap declines in the overall sample. First-generation women have about one tenth less children than natives. Although

[56] Adding interaction terms for age do not affect the overall findings.

significant, the change is small in magnitude and hides patterns in the subsamples. Conditioning on households that do not achieve their ideal outcomes does not change the fertility differential between second-generation and native women. Both groups of women prefer mixed-sex children and respond similarly when the ideal is not achieved. Additionally, the fertility gap is similar across generations, indicating that assimilation does not occur. Not only is the estimate (0.022) insignificant, it is also small in magnitude.

Conditioning on households with ideal outcomes may increase or decrease the estimated fertility differentials. For example, if first-generation immigrant women are relatively more likely to stop having children if they get their ideal outcome (a son), then the fertility gap would be larger than 0.176. The regression results in Column 3 compare first-generation households with at least one son, with native households with mixed-sex children. Similarly, second-generation and native households are compared if they have mixed-sex children. Not surprisingly, the first-native gap is much larger in magnitude than the previous first-generation and native comparisons, while the second-generation and native gap is unchanged. Across generations, there appears to be large changes in the fertility differentials. The fertility gap decreases substantially and provides strong evidence for fertility assimilation.

The estimates in Column 2 find insignificant results for fertility assimilation across generations, while the estimates in Column 3 provide significant evidence for fertility assimilation. Although the initial decline in the fertility gap of 0.075 children across generations is significant, it poorly describes the large changes in fertility behavior among households that achieve the ideal sex composition.

Kahn (1994) finds relatively low fertility among immigrants from China, India, and Korea and attributes it to selectivity. She notes that "because of their high levels of education and income, they probably would have had lower fertility than their home country populations, even if they never had migrated." As I have shown, first-generation women have relatively lower fertility levels if they have at least one son.[57] Additionally, I find that my fertility assimilation results are robust to controlling for education, employment, intermarriage, and ethnic enclave residence (Table 5). There appear to be large changes in fertility behavior across generations for households that achieve their ideal outcome in all specifications. First-generation women who do not have a son have more children and close the fertility gap.[58]

3.5 DISCUSSION

I previously showed that across immigrant generations, child-sex preferences evolve from a desire to have a son to a desire for mixed sibling children.[59] In this section, I use Bisin and Verdier's (2000, 2001) economic model of cultural transmission to motivate possible explanations for why this change in preferences occurs,[60] supplemented with empirical evidence from the economics and sociology literatures. I then present some

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[57] Friedberg (2000) shows that the origin of an individual's education and experience is important. Human capital acquired abroad is valued less than human capital acquired in the U.S. Kahn (1994) does not discuss where the education was obtained.

[58] Although not shown, patterns across age groups are consistent with the estimates in Table 4. The full interaction results can be found in Appendix 5.

[59] Almond et. al (2013) study of Canadian immigrants find similar results; however, they do not discuss the possible sources for the generational change in preferences.

[60] Cavalli-Sforza and Feldman (1981) and Boyd and Richerson (1985) were the first to propose models of cultural transmission in their seminal work in evolutionary anthropology. More recently, economists have shown interest in studying the dynamics of beliefs, norms, and preferences as endogenous to socioeconomic status. Various empirical studies of the perceived importance of education, the interdependence of agents' consumption and production patterns, and the relevance of ethnic and religious values suggest that preferences evolve endogenously. (Borjas, 1992; Duesenberry, 1949; Kapteyn et al., 1980; Iannaccone, Pollak, 1976)

descriptive statistics to determine the validity of these channels for the immigrant group studied in this paper.

Bisin and Verdier (2000, 2001) develop a model of preference evolution based on the interaction of (direct) parental socialization and (oblique) socialization processes outside the family. Cultural transmission is the transmission of preferences, beliefs, and norms due to interactions within and across generations. In the context of this paper, son preference is transmitted through parents while the oblique transmission encourages the mixed child-sex preference. Intuitively, in a society with two traits, if immigrant parents are unable to instill their own trait through direct socialization, their children are likely to acquire the native trait through oblique socialization. The degree of parent effort in socialization is endogenous to socioeconomic factors. I discuss some of the factors below, including potential labor market outcomes, education outcomes, ethnic enclave residence, and intermarriage.[61]

In the model, a parent receives utility from his or her child's future socioeconomic action. This is closely related to one of the reasons why son preference exists. Miller (1981), Chung and Das Gupta (2007) and Guilmoto (2009) show that in old age, parents rely heavily on sons for financial support.[62] If immigrant parents perceive higher potential wages or improved work opportunities for their daughters, then the financial motivation to

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[61] It is important to note that none of the discussion is causal, nor can I objectively rank the factors by degree of influence.

[62] These papers use data from China, India, or South Korea. However, Almond et. al (2013) suggest that son preference may be vulnerable to the "higher social and economic status of women" (p. 18). In addition to the financial motivation, there is also an emphasis on the cultural value associated with sons. According to tradition, lineage is traced through the male. This would counteract the decline of son preference across generations; however, mixed child-sex households still have a son. To explain the change in preferences, I do not have to eliminate lineage through the male, I only have to show that daughters are also preferred.

have a son declines as the opportunity cost of having a daughter declines.[63] Also, if potential wages are positively correlated with education, then improvement in future education outcomes for daughters may also increase the desire to have a daughter.

Additionally, higher education levels are correlated with the amount of time spent outside of the family home and possibly increase the likelihood of being in an environment that encourages the mixed-sex preference. Cohen (1977) finds that people with higher levels of education may have spent more time among individuals of different backgrounds which decreases aversion to others and their norms.[64] Furtado (2006) finds that individuals remain in the area they received the education and calls this the "enclave effect." In the context of Bisin and Verdier's model, if highly educated individuals spend more time outside of the home then oblique transmission is relatively more influential in determining someone's preference.

The ethnicity of the spouse may affect the effort a parent exerts in transmitting the cultural predisposition for sons. Although Bisin and Verdier's model limits households to one parent and one child, I suggest that parents who share the same cultural preference for a son collectively exert more effort in transmitting that trait compared to intermarried households.[65] On the other hand, if a second-generation woman forms her child-sex preferences in her childbearing years (after marriage), then the ethnicity of her spouse may

[63] Edlund and Lee (2009) model son preference in developing countries and suggest that imbalanced male to female sex ratios will decline as the economy develops. One of the potential channels is the relative performance of women in the labor market. A major critique of this paper is that son preference still exists in developed countries (U.S. and Canada).
[64] Kalmijn (1998) suggests that highly educated individuals are less likely to be attached to their community because they left their ethnic environment for school.
[65] Children of mixed marriages are less likely to maintain cultural distinctions because they are less likely to identify with a single ethnic group (Kalmijn, 1998).

be relatively more influential. For example, even though a second-generation Indian female was raised by two Indian parents, if her spouse is from a different culture, then the likelihood of son preference may decline.[66]

Finally, ethnic enclave residence also augments the effectiveness of direct transmission through the parents. Assuming that son preference exists within ethnic enclaves, a child raised in this environment is more likely to exhibit that trait. The direct and oblique socialization processes are complementary in that they both encourage a preference for sons. However, timing of transmission is unclear and is not discussed in the model nor in the son preference literature. For example, assume that second-generation immigrants form their child-sex preferences at older ages when they are in their childbearing years. If they no longer live in ethnic enclaves during that time period, then they are in an environment where the direct and oblique mechanisms are substitutes, which lowers the likelihood of adopting a desire for sons. Tables 6 through 9 provide some descriptive evidence to corroborate the possible channels outlined above. I interact with employment, education, intermarriage, and ethnic enclave residence individually in equation (1). The full interaction results can be found in the Appendix 4 through 7.

Table 6 determines if employed women differ in their fertility behavior to test the hypothesis that son preference declines as a result of improved opportunities for female labor market outcomes. I make the assumption that households with working mothers are more optimistic for the potential labor market outcome of their daughter. If this is the case, then I expect to find weaker evidence for son preference in households with employed

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[66] More generally, empirical evidence suggests intermarriage is correlated with assimilation (Meng and Gregory, 2005; Meng and Meurs, 2006; Kantarevic, 2004).

women. The estimates are similar in significance and magnitude to those in Table 2. I do not find evidence that employed first-generation women are less likely to exhibit a preference for sons.

The effects of working mothers may have a delayed effect in that their influence may appear in the second-generation outcomes. Studies show that among immigrant women, the mother's employment status is correlated with the daughter's future outcome. Similarly, men raised in households with employed mothers are more likely to marry a woman who works (Fernandez, Fogli, and Olivetti 2002). Thus, both sons and daughters in these households may have improved perceptions about the labor market outcomes for females which lessens the demand for sons among the second-generation. Ideally, I would disaggregate second-generation households by whether or not they were raised in households that had a working mother, but this is not possible with the data used in this paper.

The estimates in Tables 7a look at the fertility behavior among college educated women. Although there is still evidence for son preference among first-generation women, the estimates are all smaller in magnitude compared to the overall sample in Table 2. The estimates in Table 7a require that women have some college education. However, it is likely that the oblique transmission is stronger for women who have spent more years in a college environment. Table 7b looks at first-generation women by degree. Panel A is for first-generation women with some college education, Panel B conditions on earning a bachelor's degree, and Panel C conditions on a master's degree or higher.[67] Across all

[67] Among first-generation women across all years, about 77 percent have some college education, 63 percent have at least a bachelor's degree, and 30 percent have at least a master's degree.

specifications, there is evidence for son preference. However, as the level of attainment rises, the evidence for son preference weakens in magnitude.

Among married first-generation women, over 83 percent have husbands from the same cultural background. With such few women marrying outside of their ethnic group, I do not anticipate intermarriage among first-generation households to drive the decline of son preference. The estimates in Table 8, Panel B yield similar results compared to the overall sample.[68] As I mentioned previously, the ethnicity of the spouse for second-generation women may also be a contributing factor. Intermarriage is much more common for second-generation women with only 42 percent marrying men from the same ethnic group. If preferences about child-sex composition are formed after marriage, then I expect there to be weaker evidence for the mixed sibling-sex preference among second-generation women who did not intermarry. On the other hand, if preferences are formed prior to marriage, it is possible that the reasons for the decline in son preference may also explain the rise in intermarriage rates. The estimates in Table 8, Panel C show that second-generation women who married within their culture still exhibit the preference for mixed-sex children. Interestingly, the estimates are larger in magnitude, indicating stronger evidence for the mixed preference.

If I assume that child-sex preferences are developed at younger ages, then I would want to analyze childbearing behavior of second-generation women based on whether or not they were raised in an ethnic enclave. On the other hand, if I assume that preferences are adopted during childbearing years, then the current location of a second-generation

[68] The results in Table 8 condition on households where the parents have the same cultural background. Restricting the sample to intermarriage household (especially for the first-generation) reduces the sample substantially.

woman is important. I cannot test the first statement; however, I can determine if the evidence for son preference is stronger for first-generation women who live in ethnic enclaves. I adopt Bleakley and Chin's (2010) method to examine residential location outcomes. Using the lowest level of geographic aggregation measured in this data, PUMAs (public-use microdata area) which contain at least 100,000 individuals, I construct two dummy variables for ethnic enclave residence. The first is based on whether or not a woman lives in a PUMA with at least 5 percent of residents from the same country of birth (Table 9, Panels A and B). The second dummy is more restrictive and requires 10 percent of residents born abroad (Table 9, Panels C and D).[69]

The evidence for son preference among first-generation women who live in ethnic enclaves is stronger. Women from China, India, or South Korea are significantly more likely to have a second child if the first born is a daughter, which was not the case in Table 2. Additionally, the coefficients in Column (4) are insignificant. If preferences are formed at older ages, then I might expect to find weaker evidence for the mixed-sex preference among second-generation women who live in ethnic enclaves. The coefficients in Panels B and D for second-generation women are insignificant. This is likely due to small sample sizes. Only 20 percent of second-generation women live in PUMAs with at least 5 percent of residents who share their ancestry (compared to 50 percent of first-generation women).

I cannot attribute the overall decline in son preference to any single factor. I have briefly discussed that a woman's employment, education, intermarriage, and ethnic enclave outcomes may affect her effort and corresponding success in transmitting the desire for

[69] Admittedly, this is a poor measure for ethnic enclave. I would ideally be able to identify neighborhood characteristics based on areas with fewer people. It is likely that the coefficients in the Table 9 do not adequately capture the full impacts of living in ethnic enclaves.

sons. In some cases, I find evidence consistent with economic explanations of the decline in son preference. They don't seem to account for much of the decline in the aggregate, which could be because I do not fully capture these variables, like the expectations for daughter's employment, or because it is driven by culture, not economics.

3.6 CONCLUSION

This paper shows the persistence of son preference among first-generation Chinese, Indian, or Korean immigrants. Child-sex composition preferences change in the second-generation toward a preference for mixed sibling children (similar to natives). Using these preferences, I then disaggregate households by composition to determine if fertility assimilation conclusions are affected. I find large fertility differentials between first-generation households that achieved a son (their ideal outcome) and native households with mixed-sex children. First-generation households are more likely to stop having children if their desired outcome is achieved compared to native households that achieve their ideal mixed-sex outcome.

The fertility differential is small in magnitude for households that did not achieve the ideal child-sex compositions (only daughters for first-generation households and same sex children for native households). To evaluate if assimilation occurs, I compare the first-generation and native fertility gap with the second-generation and native fertility gap. Conditioning on households that achieved their ideal outcomes, I find strong evidence for assimilation across generations.

Table 3.1: Descriptive Statistics for Adult Women with At Least One Child

	U.S. born women 1990		U.S. born women 2006-2012		Women from China, India, or Korea 1990		Second Generation Women from China, India, or Korea 2006-2012	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std. Dev.
Age	35.89	7.38	38.39	7.49	36.13	6.42	37.96	6.9
Age at first birth	24.17	4.78	26.34	5.44	27.71	4.13	29.17	5.46
Age at second birth*	26.77	4.65	29.05	5.17	30.21	4.1	31.67	5.04
Years of education	6.9	1.96	7.69	2.07	8.04	2.64	9.12	2
Bachelor's degree dummy	0.18	0.38	0.32	0.47	0.47	0.5	0.65	0.48
Married dummy	0.81	0.39	0.76	0.43	0.96	0.21	0.88	0.32
Intermarried dummy	0.03	0.16	0.05	0.22	0.17	0.37	0.58	0.49
Employed dummy	0.67	0.47	0.71	0.45	0.62	0.48	0.7	0.46
Usual hours worked per week	35.05	13.03	36.88	11.16	37.09	14.26	37.21	12.43
Husband's usual hours worked per week	43.78	12.87	42.81	13.87	44.58	13.66	43.25	13.96
Total family income	56,824	46,414	84,207	80,729	81,633	68,479	143,159	131,241
Wage and salary income	19,853	17,629	35,219	35,704	26,977	29,019	58,417	61,948
Husband's wage and salary income	40,976	36,952	62,124	66,625	49,940	48,491	96,762	98,671
Number of own children in household	1.95	0.97	1.93	0.96	1.76	0.75	1.83	0.85
First child is female	0.48	0.5	0.48	0.5	0.49	0.5	0.49	0.5
First two children are female*	0.23	0.42	0.23	0.42	0.24	0.43	0.24	0.43
First two children are mixed sex*	0.5	0.5	0.5	0.5	0.51	0.5	0.49	0.5
# Observations (1+ child)	1,723,173		1,704,011		13,560		7,971	
# Observations (2+ children)	1,087,830		1,068,498		8,183		4,863	

Notes: Weekly hours, and wage and salary income variables are conditional on employment. Family income and wage and salary income values are in 2009 dollars. The intermarried dummy is based on sharing the same race or ancestry for native households. *Conditional on having at least two children.

Table 3.2a: Fertility Behavior by Sex of First Child or First Two Children

	Indicator for:				
	First Born Female	Two Females	Mixed Sex	Mixed Sex*	Mixed Sex**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
A. Native Women					
Has Two or More Children	0.001				
	(0.001)				
Has Three or More Children		0.006***	-0.060***	-0.058***	-0.064***
		(0.001)	(0.001)	(0.001)	(0.001)
B. First-Generation Women From China, India, or South Korea					
Has Two or More Children	0.013				
	(0.008)				
Has Three or More Children		0.109***	-0.077***	-0.023*	-0.132***
		(0.014)	(0.009)	(0.011)	(0.011)
C. Second-Generation Women From China, India, or South Korea					
Has Two or More Children	-0.007				
	(0.011)				
Has Three or More Children		-0.023	-0.036**	-0.044**	-0.027
		(0.019)	(0.013)	(0.015)	(0.016)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female. Estimates for native women use 1990 data. The results are consistent in the more recent data. Information about the first-generation is obtained using 1990 data and second-generation information is from the 2006 to 2012 data.

Table 3.2b: Evidence for Son Preference by Country of Birth

	Indicator for:				
	First Born Female	Two Girls	Mixed Sex	Mixed Sex*	Mixed Sex**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
A. First-Generation Women from China					
Has Two or More Children	0.013				
	(0.013)				
Has Three or More Children		0.087***	-0.092***	-0.051**	-0.136***
		(0.022)	(0.014)	(0.017)	(0.018)
B. First-Generation Women From India					
Has Two or More Children	0.040**				
	(0.015)				
Has Three or More Children		0.130***	-0.067***	0.001	-0.128***
		(0.026)	(0.017)	(0.020)	(0.021)
C. First-Generation Women from South Korea					
Has Two or More Children	-0.013				
	(0.016)				
Has Three or More Children		0.123***	-0.065***	-0.009	-0.129***
		(0.025)	(0.016)	(0.018)	(0.021)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table 3.2c: Evidence for Son Preference by Ancestry

	Indicator for:				
Dependent Variable:	First Born Female (1)	Two Girls (2)	Mixed Sex (3)	Mixed Sex* (4)	Mixed Sex** (5)
A. Second-Generation Chinese Women					
Has Two or More Children	-0.012				
	(0.015)				
Has Three or More Children		-0.031	-0.041*	-0.057**	-0.025
		(0.025)	(0.017)	(0.020)	(0.021)
B. Second-Generation Indian Women					
Has Two or More Children	0.026				
	(0.026)				
Has Three or More Children		0.007	-0.053	-0.045	-0.057
		(0.043)	(0.029)	(0.036)	(0.034)
C. Second-Generation South Korean Women					
Has Two or More Children	-0.023				
	(0.025)				
Has Three or More Children		-0.042	-0.025	-0.042	-0.005
		(0.045)	(0.031)	(0.038)	(0.038)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table 3.3: Male to Female Sex Ratios at Birth

	Natives, 1990	First-Generation	Second-Generation
First Child	1.08	1.04	1.04
Second Child	1.06	1.00	1.04
Conditional on female first born	1.04	1.02	1.02
Conditional on female first born & nchild=2	1.14	1.21	1.08
Conditional on male first born	1.07	1.03	1.07
Conditional on male first born & nchild=2	1.00	1.03	1.02
Third Child	1.06	1.09	0.97
Conditional on female 1st & 2nd	1.02	1.11	1.32
Conditional on female 1st & 2nd & nchild=3	1.06	1.24	1.59
Conditional on male 1st & 2nd	1.08	1.04	0.86
Conditional on male 1st & 2nd & nchild=3	1.04	1.02	0.80

Notes: Nchild refers to the number of children in the household. First and second-generation immigrants refer to women of Chinese, Indian, or Korean ancestry. Estimates for native women are displayed for the 1990 sample. Information about the first-generation is from 1990 data and second-generation information is from 2006-2012 data.

Table 3.4: Assimilation Results

	Overall	Non-Ideal	Ideal
First-Generation Indicator	-0.176***	-0.128***	-0.581***
	(0.004)	(0.009)	(0.004)
Second-Generation Indicator	-0.100***	-0.106***	-0.097***
	(0.011)	(0.017)	(0.016)
Difference	-0.075***	-0.022	-0.484***
	(0.011)	(0.019)	(0.017)

Notes: * p<0.05, ** p<0.01, *** p<0.001. All regressions control for age, ancestry, year, and state fixed effects. An ideal outcome for a first-generation household is that there is at least one son. For second-generation and native households, the ideal outcome is achieved if there is a son and daughter.

Table 3.5a: Assimilation and Adaptation Results for the Pooled Sample with Controls

	X = Employed			X = College		
	Overall	Ideal	Non-Ideal	Overall	Ideal	Non-Ideal
First-Generation * X	0.179***	0.115***	0.128***	-0.228***	-0.130***	-0.222***
	(0.008)	(0.008)	(0.018)	(0.009)	(0.009)	(0.020)
Second-Generation * X	0.068**	0.064	0.115***	-0.072*	-0.097*	-0.116**
	(0.023)	(0.034)	(0.035)	(0.028)	(0.044)	(0.043)
First-Generation Indicator	-0.314***	-0.672***	-0.226***	0.001	-0.475***	0.042*
	(0.006)	(0.006)	(0.014)	(0.008)	(0.008)	(0.017)
Second-Generation Indicator	-0.148***	-0.142***	-0.185***	-0.035	0.003	0.008
	(0.019)	(0.028)	(0.029)	(0.026)	(0.040)	(0.039)
X	-0.276***	-0.234***	-0.240***	-0.032***	-0.098***	-0.100***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	2.144***	2.548***	2.633***	2.022***	2.492***	2.572***
	(0.008)	(0.011)	(0.012)	(0.008)	(0.012)	(0.012)
Difference+	-0.055***	-0.478***	-0.028	-0.120***	-0.511***	-0.071***
	(0.014)	(0.020)	(0.023)	(0.013)	(0.018)	(0.021)

Notes: * p<0.05, ** p<0.01, *** p<0.001. All regressions control for age, ancestry, year, and state fixed effects. An ideal outcome for a first-generation household is that there is at least one son. For second-generation and native households, the ideal outcome is achieved if there is a son and daughter. + Estimates the change in the fertility gap across generations conditional on the corresponding control variable.

Table 3.5b: Assimilation and Adaptation Results for the Pooled Sample with Controls

	X = Husband Same Culture			X = Ethnic Enclave Residence		
	Overall	Ideal	Non-Ideal	Overall	Ideal	Non-Ideal
First-Generation * X	0.049***	0.070***	0.038	0	-0.008	-0.050*
	(0.013)	(0.014)	(0.031)	(0.010)	(0.012)	(0.022)
Second-Generation * X	0.028	0.038	0.098**	-0.017	-0.031	-0.056
	(0.023)	(0.034)	(0.035)	(0.033)	(0.047)	(0.052)
First-Generation Indicator	-0.264***	-0.638***	-0.172***	-0.170***	-0.574***	-0.112***
	(0.013)	(0.013)	(0.030)	(0.004)	(0.005)	(0.010)
Second-Generation Indicator	-0.140***	-0.146***	-0.167***	-0.096***	-0.090***	-0.098***
	(0.015)	(0.023)	(0.023)	(0.012)	(0.017)	(0.018)
X	0.007	-0.034***	-0.012*	-0.033***	-0.033***	-0.025**
	(0.004)	(0.005)	(0.006)	(0.005)	(0.007)	(0.008)
Constant	2.041***	2.432***	2.520***	2.002***	2.454***	2.539***
	(0.010)	(0.014)	(0.015)	(0.008)	(0.012)	(0.012)
Difference+	-0.103***	-0.461***	-0.065*	-0.057	-0.460***	-0.008
	(0.018)	(0.025)	(0.027)	(0.031)	(0.044)	(0.052)

Notes: * p<0.05, ** p<0.01, *** p<0.001. All regressions control for age, ancestry, year, and state fixed effects. An ideal outcome for a first-generation household is that there is at least one son. For second-generation and native households, the ideal outcome is achieved if there is a son and daughter. + Estimates the change in the fertility gap across generations conditional on the corresponding control variable.

Table 3.6: Fertility Behavior – Employed Women

	Indicator for:				
	First Born Female	Two Girls	Mixed Sex	Mixed Sex*	Mixed Sex**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
A. Native Women					
Has Two or More Children	-0.005***				
	(0.001)				
Has Three or More Children		0.001	-0.056***	-0.055***	-0.056***
		(0.002)	(0.001)	(0.001)	(0.001)
B. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.020***				
	(0.005)				
Has Three or More Children		0.109***	-0.077***	-0.025**	-0.134***
		(0.009)	(0.006)	(0.008)	(0.008)
C. Second-Generation Women from China, India, or South Korea					
Has Two or More Children	-0.012				
	(0.013)				
Has Three or More Children		-0.035	-0.041*	-0.057**	-0.022
		(0.024)	(0.016)	(0.020)	(0.020)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table 3.7a: Fertility Behavior – College Educated Women

	Indicator for:				
	First Born Female	Two Girls	Mixed Sex	Mixed Sex*	Mixed Sex**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
A. Native Women					
Has Two or More Children	-0.007***				
	(0.001)				
Has Three or More Children		-0.004*	-0.057***	-0.058***	-0.055***
		(0.002)	(0.001)	(0.001)	(0.001)
B. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.021***				
	(0.004)				
Has Three or More Children		0.072***	-0.057***	-0.023**	-0.095***
		(0.008)	(0.006)	(0.007)	(0.007)
C. Second-Generation Women from China, India, or South Korea					
Has Two or More Children	-0.012				
	(0.012)				
Has Three or More Children		-0.019	-0.043**	-0.052**	-0.033
		(0.021)	(0.015)	(0.018)	(0.018)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table 3.7b: Fertility Behavior – College Educated Women

	Indicator for:				
Dependent Variable:	First Born Female (1)	Two Girls (2)	Mixed Sex (3)	Mixed Sex* (4)	Mixed Sex** (5)
A. First-Generation Women with Some College					
Has Two or More Children	0.021***				
	(0.004)				
Has Three or More Children		0.072***	-0.057***	-0.023**	-0.095***
		(0.008)	(0.006)	(0.007)	(0.007)
B. First-Generation Women with at least a Bachelor's Degree					
Has Two or More Children	0.019***				
	(0.004)				
Has Three or More Children		0.062***	-0.048***	-0.019*	-0.081***
		(0.009)	(0.006)	(0.008)	(0.008)
C. First-Generation Women with at least a Master's Degree					
Has Two or More Children	0.009				
	(0.006)				
Has Three or More Children		0.051***	-0.045***	-0.021	-0.072***
		(0.014)	(0.009)	(0.011)	(0.012)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table 3.8: Fertility Behavior – Husband has Same Cultural Background

Dependent Variable:	First Born Female (1)	Two Girls (2)	Mixed Sex (3)	Mixed Sex* (4)	Mixed Sex** (5)
	Indicator for:				
A. Native Women					
Has Two or More Children	-0.003***				
	(0.001)				
Has Three or More Children		0.001	-0.060***	-0.059	-0.062
		(0.002)	(0.001)	(0.002)	(0.002)
B. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.017***				
	(0.004)				
Has Three or More Children		0.104***	-0.072***	-0.022***	-0.126***
		(0.008)	(0.005)	(0.006)	(0.007)
C. Second-Generation Women from China, India, or South Korea					
Has Two or More Children	-0.015				
	(0.018)				
Has Three or More Children		0.004	-0.046*	-0.044	-0.048
		(0.032)	(0.022)	(0.026)	(0.027)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female. Estimates for native women use 1990 data. The results are consistent in the more recent data as well.

Table 3.9: Fertility Behavior – Women in Ethnic Enclaves

	Indicator for:				
	First Born Female	Two Girls	Mixed Sex	Mixed Sex*	Mixed Sex**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
A. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.031***				
	(0.008)				
Has Three or More Children		0.111***	-0.070***	-0.017	-0.128***
		(0.015)	(0.010)	(0.012)	(0.013)
B. Second-Generation Women from China, India, or South Korea					
Has Two or More Children	0.014				
	(0.030)				
Has Three or More Children		-0.013	-0.029	-0.035	-0.022
		(0.055)	(0.037)	(0.044)	(0.046)
C. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.048***				
	(0.013)				
Has Three or More Children		0.094***	-0.078***	0	-0.126***
		(0.023)	(0.016)	(0.026)	(0.019)
D. Second-Generation Women from China, India, or South Korea					
Has Two or More Children	0.055				
	(0.051)				
Has Three or More Children		-0.063	-0.044	-0.053	-0.034
		(0.092)	(0.066)	(0.080)	(0.081)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Panels A and B define an ethnic enclave as a PUMA with at least 5 percent of residents born in China, India, or South Korea. Panels C and D require at least 10 percent be from these source countries. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

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CHAPTER 1 APPENDIX

Table A.1: School Characteristics by Number of Counselors

	Number of Counselors	Number of Teachers	Enrollment	% FRPM	% Hispanic	% English Learners	Academic Performance Index	Overall Dropout Rate
	0	258.1	1169.1	0.5	0.4	0.2	712.8	2.4
	1	196.3	819.2	0.5	0.5	0.3	725.8	2.1
	2	253.1	1135.0	0.5	0.5	0.3	732.7	1.6
	3	326.1	1488.7	0.4	0.4	0.3	740.4	1.6
	4	401.3	1871.3	0.4	0.4	0.3	745.0	1.5
	5	443.2	2090.0	0.5	0.5	0.3	737.5	1.7
	6	504.8	2383.9	0.5	0.5	0.3	735.0	1.8
	7+	603.4	2875.7	0.5	0.6	0.3	699.7	2.7
Mean:	4	380.8	1766.4	0.5	0.5	0.3	728.2	1.9
Correlation with # Counselors:		0.6	0.7	0.1	0.2	0.2	0.0	0.1

Notes: Annual dropout rates measure the number of dropouts throughout the year divided by the number of students enrolled at the beginning of the academic year. Dropouts do not include students who transferred to another public school or district. Grade 12 Graduation Rate is the share of enrolled 12th grade students who graduate.

Table A.2: Dropout Rate Results with Additional Covariates, 2003-04 through 2006-07

Outcome Variable:	Overall DR		Grade 12		Grade 11		Grade 10		Grade 9	
Student-to-Counselor Ratio	0.003	0.002	-0.049	-0.048	0.006	0.004	0.029	0.026	0.016	0.013
	(0.018)	(0.018)	(0.041)	(0.044)	(0.023)	(0.023)	(0.018)	(0.017)	(0.019)	(0.019)
Psychologists		-0.173**		-0.330*		-0.172**		-0.123*		-0.091
		(0.086)		(0.190)		(0.081)		(0.069)		(0.074)
Social Workers		0.132		1.196		-0.493		0.381		0.14
		(0.435)		(1.456)		(0.674)		(0.500)		(0.781)
Nurses		0.029		-0.219		0.076		0.057		-0.101
		(0.184)		(0.584)		(0.249)		(0.132)		(0.207)
Librarians		-0.078		0.348		-0.244		-0.237*		-0.177
		(0.145)		(0.371)		(0.159)		(0.131)		(0.146)
Average Prin/Vice Experience		0.026***		0.061***		0.025***		0.021***		0.021**
		(0.008)		(0.019)		(0.009)		(0.008)		(0.009)
Baseline Covariates	x	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x	x
School Fixed Effects	x	x	x	x	x	x	x	x	x	x
Additional Covariates		x		x		x		x		x
Observations	2184	2184	2116	2116	2144	2144	2174	2174	2172	2172
Adjusted R-Square	0.669	0.671	0.666	0.668	0.578	0.581	0.56	0.563	0.486	0.487

Notes: See notes for Table 4.

Table A.3: Dropout Rate Results with Additional Covariates, 2007-08 through 2014-15

Outcome Variable:	Overall DR		Grade 12		Grade 11		Grade 10		Grade 9	
Student-to-Counselor Ratio	0.017**	0.017**	0.03	0.041	0.026**	0.026**	0.005	0.006	0.01	0.009
	(0.008)	(0.008)	(0.026)	(0.029)	(0.011)	(0.011)	(0.006)	(0.006)	(0.008)	(0.009)
Psychologists		-0.002		0.198		0.024		0.036		0.001
		(0.031)		(0.201)		(0.036)		(0.028)		(0.031)
Social Workers		-0.058		0.104		-0.148		0.001		-0.158
		(0.196)		(0.719)		(0.136)		(0.095)		(0.099)
Nurses		0.05		0.237		0.047		0.018		-0.13
		(0.055)		(0.189)		(0.037)		(0.043)		(0.148)
Librarians		0.003		0.534		-0.032		-0.003		0.059
		(0.079)		(0.568)		(0.103)		(0.087)		(0.129)
Average Prin/Vice Experience		0		0.028		0.005		-0.002		-0.002
		(0.005)		(0.029)		(0.007)		(0.006)		(0.007)
Observations	6221	6221	6129	6129	6182	6182	6207	6207	6189	6189
Adjusted R-Square	0.61	0.61	0.172	0.172	0.426	0.426	0.384	0.384	0.377	0.376

Notes: See notes for Table 4.

Table A.4: California High School Exit Exam Results

	% Passed, Grade 10		% Passed, Grade 10 ELA		% Passed, Grade 10 Math	
	(1)	(2)	(3)	(4)	(5)	(6)
Student-to-Counselor Ratio	0.001	-0.018	-0.001	-0.02	0.003	-0.016
	(0.026)	(0.029)	(0.030)	(0.035)	(0.028)	(0.032)
Baseline Covariates	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x
School Fixed Effects	x	x	x	x	x	x
School Specific Trends		x		x		x
Observations	5933	5933	5933	5933	5933	5933
Adjusted R-Square	0.903	0.927	0.876	0.904	0.882	0.911

* p<0.10, ** p<0.05, *** p<0.01

Notes: Baseline covariates include percent Hispanic, percent Asian, percent black, percent free and reduced price meals, enrollment, enrollment squared, and student-to-teacher ratios. Standard errors are in parentheses and are clustered at the school level.

Table A.5: Previous Year's Dropout Rates Placebo Test Results

Dropout Outcome Variable:	2007-08 through 2014-15 Overall	Grade 12	Grade 11	Grade 10	Grade 9	2003-04 through 2006-07 Overall	Grade 12	Grade 11	Grade 10	Grade 9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Student-to-Counselor Ratio	0	-0.049*	0.019	-0.001	0.017	-0.007	0.006	-0.003	-0.082	0.011
	-0.009	-0.027	-0.021	-0.008	-0.014	-0.019	-0.034	-0.027	-0.115	-0.025
Baseline Covariates	x	x	x	x	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x	x	x	x	x
School Fixed Effects	x	x	x	x	x	x	x	x	x	x
Observations	5246	5139	5212	5233	5220	2122	2065	2088	2109	2114
Adjusted R-Square	0.714	0.436	0.128	0.578	0.423	0.689	0.707	0.3	0.084	0.55

* p<0.10, ** p<0.05, *** p<0.01

Table A.5: Truancy and Discipline Results

Outcome Variable:	Truancy (mean=716)			Discipline (mean=116)		
	(1)	(2)	(3)	(4)	(5)	(6)
Student-to-Counselor Ratio	0.827	4.31	1.489	0.811	-1.492	-1.264
	(4.066)	(6.893)	(5.939)	(0.931)	(2.010)	(3.104)
Baseline Covariates	x	x	x	x	x	x
Year Fixed Effects	x	x	x	x	x	x
School Fixed Effect		x	x		x	x
School Specific Trends			x			x
Observations	2841	2800	2800	3603	3566	3566
Adjusted R-Square	0.467	0.81	0.871	0.143	0.457	0.651

* p<0.10, ** p<0.05, *** p<0.01

Notes: Truancy and disciplinary (expulsions and suspensions) data are available beginning in academic years 2012-2013 and 2011-2012, respectively. Truancy and discipline measures report the total number of events, and do not take into account the number of unique individuals.

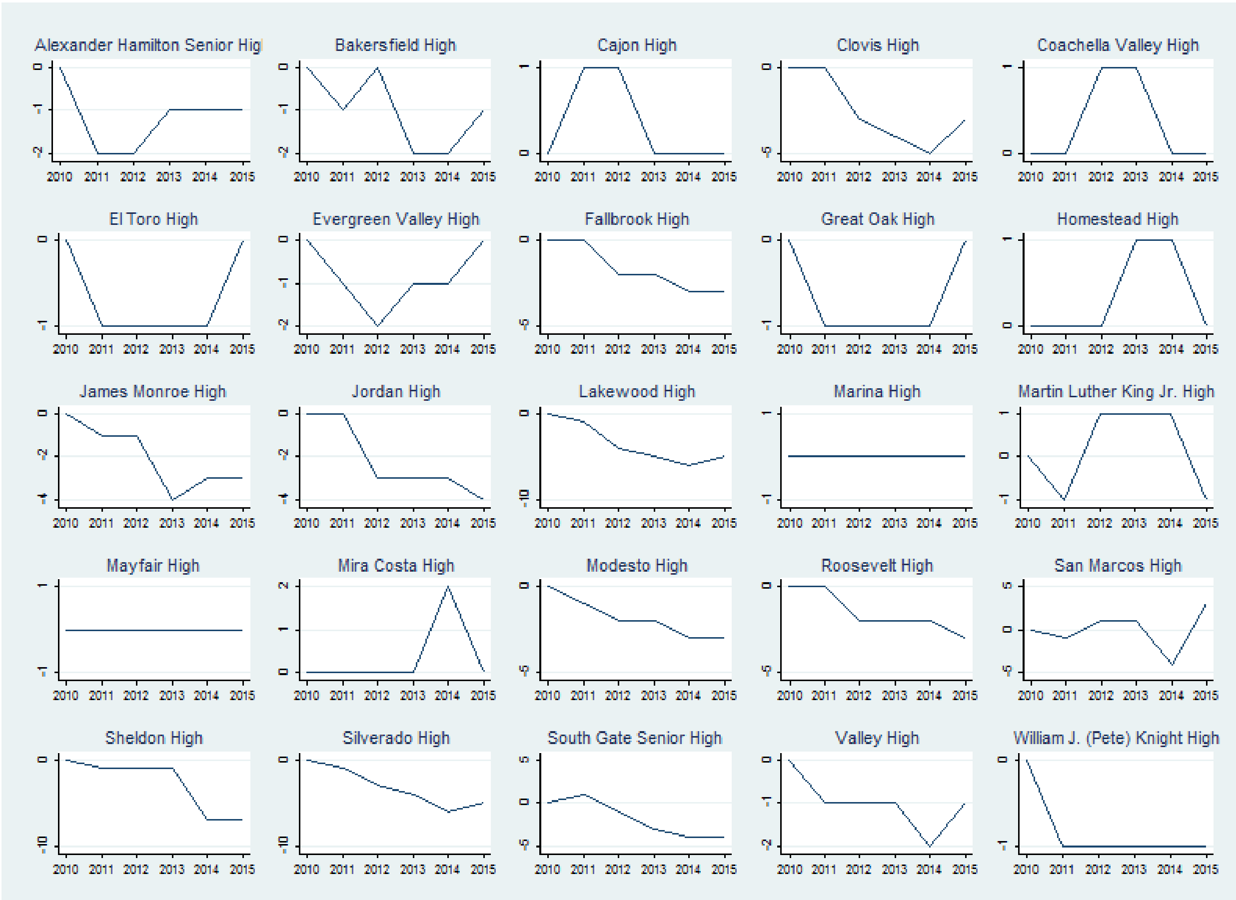
Table A.6: Dropout Intervention Literature Summary

Level	Intervention	Authors	Data	Method	Result
Early	Head Start	Ludwig and Miller (2007)	National Education Longitudinal Study (NELS88)	Regression discontinuity, exploit implementation timing	Participation in Head Start increases the probability of high school graduation by approximately 3 percentage points (4 percent).
Early	Head Start	Garces, Thomas, and Currie (2002)	Panel Study of Income Dynamics, children born in 1960s	Within-family sibling comparisons	Participation in Head Start increases the probability of high school graduation by 20 percentage points for white children (25 percent), but has no impact for black children.
Early	Head Start	Deming (2009)	Children of the National Longitudinal Survey, children born in 1980s	Within-family sibling comparisons	Participation in Head Start increases the probability of high school graduation by 11 percentage points for males and by 13 percentage points for children of mothers with low cognitive skills.
Early	Subsidized child care	Havnes and Mogstad (2011)	Norway, 1967-1976 births	1975 reform, difference-in-differences	Subsidized child care during the preschool years reduces the probability of dropping out of high school by 7 percentage points for children whose mothers had not graduated from high school, corresponding to 26 percent.
Elementary	Class size and quality	Murnane (2013)	Tennessee STAR Experiment, 1985-1989	Random assignment of students and teachers to	Assignment to a small class for the first year in school increases the probability of high school graduation by 9 percentage points (15 percent) for black male children, and by 7

				classrooms within schools	points (11 percent) for male children from low-income families
Elementary/Middle	Teacher quality	Chetty, Friedman and Rockoff (2011)	School district data from grades 3-8 for 2.5 million students linked to tax records on parent characteristics and future outcomes	Teacher turnover variation	Students assigned to high value-added teachers are more likely to attend college and to have higher earnings than children assigned to lower value-added teachers.
Middle	School grade change	Bedard and Do (2005)	Common Core of Data, 1987-1994	District fixed effects	Moving from a system in which students change schools at the end of grade 6 to a system where they change schools at the end of grade 5 reduces the on-time high school graduation rate by 1 percent to 3 percent.
Middle	School grade change	Schwerdt and West (2013)	Florida public schools, grades 3-10, 2000-2009	Student fixed effects, instrumental variables	Students who attend an elementary school ending in grade 5, and change schools in grade 6 and again after grade 8, have a 1.4 percentage point (14.5 percent) higher dropout rate between grades 9 and 10 than students who attend a K-8 elementary school
High School	School choice	Deming et al. (2011)	Charlotte-Mecklenburg, North Carolina administrative data matched to	Lotteries allow winners to choose public high school	Enrolling in a public high school of choice increases the probability of high school graduation by 16 percent among students living in

			National Student Clearinghouse data, 2002		neighborhoods served by low quality high schools.
High School	Major school reform	Kemple, Herlihy, and Smith (2005)	Talent Development High School Model, 5 high schools in Philadelphia following 20 cohorts, began in 1998	Interrupted time series, match schools to similar Philadelphia schools without the program	Increases the rate of on-time graduation by 8 percentage points in the two earliest implementing schools (the only schools in which students were tracked long enough to observe high school graduation rates)
High School	Major school reform	Bloom, Unterman (2012)	New York City, 2002-2008	Lotteries determine access to the 105 oversubscribed small schools with no academic admission requirements	New York City closed more than twenty large low-performing high schools and opened more than two-hundred small schools in their place. Enrolling in one of the 105 oversubscribed small schools of choice increased the four-year high school graduation rate of students from 59 to 68 percent.

Figure A.1: Within School Counseling Variation, 25 Randomly Selected Schools, 1st Quartile



Notes: I randomly select 100 schools and group them into four categories based on average enrollment. The largest 25 schools have 5.4 counselors and 2,788 students, on average. The second largest group of schools has 4.9 counselors and 2,012 students, on average. The third largest group of schools has 3.5 counselors and 1,268 students, on average. Finally, the smallest set of 25 schools has 1.2 counselors and 364 students, on average. The figures are normalized to begin at zero at the start of the period.

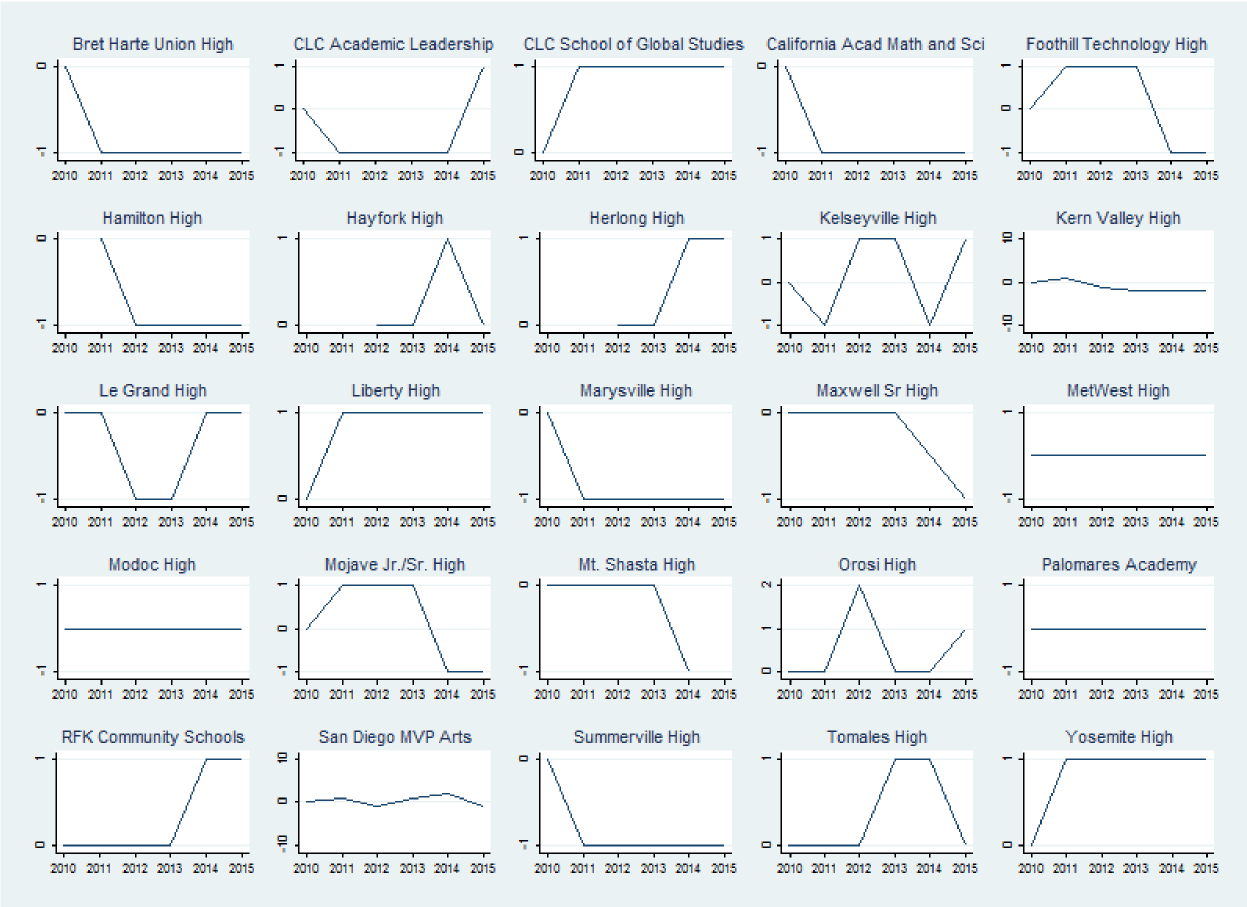
Figure A.2: Within High School Counseling Variation, 25 Randomly Selected Schools, 2nd Quartile

Notes: See Figure A.1 notes.

Figure A.4: Within High School Counseling Variation, 25 Randomly Selected Schools, 3rd Quartile

Notes: See Figure A.1 notes.

Figure A.5: Within High School Counseling Variation, 25 Randomly Selected Schools, 4th Quartile



Notes: See Figure A.1 notes.

CHAPTER 2 APPENDIX

Table A.1: Science Fair Category Descriptions

Category	Description
Aerodynamics/ Hydrodynamics	Studies of aerodynamics and propulsion of air, land, water, and space vehicles; aero/ hydrodynamics of structures and natural objects. Studies of the basic physics of fluid flow.
Alternative Energy & Power	Studies of power generation using alternative energy technologies such as solar cells.
Applied Mechanics & Structures / Manufacturing	Studies concerning the design, manufacture, and operation of mechanisms, including characteristics of materials, dynamic response, and active/ passive control. Testing for strength and stiffness of materials used to provide structural capability; studies and testing of structural configurations designed to provide improved weight and force loading or stiffness capabilities.
Behavioral & Social Sciences	Studies of human psychology, behavior, development, linguistics, and the effects of chemical or physical stress on these processes. Experimental or observational studies of attitudes, behaviors, or values of a society or groups within a society, and of the influences of society on group behavior. Includes gender and diversity studies, anthropology, archaeology, and sociology. Studies may focus on either normal or abnormal behavior.
Biochemistry/ Molecular Biology	Studies at the molecular, biochemical, or enzymatic levels in animals (including humans), plants, and microorganisms, including yeast. Studies of biological molecules, e.g., DNA, RNA, proteins, fats, vitamins, nutrients.
Chemistry	Studies in which chemical properties of nonbiological organic and inorganic materials (excluding biochemistry) are observed. Some studies involving physical properties are appropriate, including phase changes, crystal structures and formation, intermolecular and intramolecular forces.
Cognitive Science	Studies of learning, memory, and cognition in humans, using human or animal models for human processes. Studies of the effects of chemical or physical stress on cognition. Includes projects on subliminal perception, optical illusions, recall and observations (e.g. reliability of eyewitnesses), and the interaction of different senses.

Earth & Planetary Sciences / Physical Environments	Studies in surficial geology, geophysics, seismology, engineering geology, earthquake engineering, atmospheric physics, physical oceanography, marine geology, coastal processes, and comparative planetology. Studies of environmental factors not related to living things, and of the effects of human activity on naturally occurring physical phenomena.
Electronics & Electromagnetics	Experimental or theoretical studies with electrical circuits, computer design, electro-optics, electromagnetic applications, and antennas.
Environmental Engineering	Projects which apply technologies such as recycling, reclamation, restoration, composting, and bioremediation which could benefit the environment and/or the effects of pollution on the environment.
Environmental Science	Projects surveying, measuring, or studying the impact of natural and man-made changes on the environment. Examples include: floods, fires, biohazardous spills, acid rain, earthquakes, air pollution, and water pollution.
Mammalian Biology	Studies of growth and developmental biology, anatomy, and physiology in all mammals, including humans. Studies of the behavior of all mammals in their natural habitats (or reproductions of them).
Materials Science	Studies of materials characteristics and their static (not in motion) physical properties. Includes measurements and comparisons of materials durability, flammability, and insulation properties (thermal, electrical, acoustic, optical, electromagnetic, etc.).
Mathematics & Software	Studies in geometry, topology, real and complex analysis, number theory, algorithm analysis and optimization, artificial intelligence, computability, computer graphics, modeling and simulation, programming environments and languages.
Microbiology (General)	Studies of genetics, growth, and physiology of bacteria, fungi, protists, algae, or viruses. Includes surveys of bacterial contamination. Senior Division Only: includes projects described within the category Microbiology (Medical).
Microbiology (Medical)	Studies of prevention, diagnosis, and treatment of infectious diseases caused by pathogenic bacteria, fungi, or viruses. Includes all antimicrobial studies except testing of commercial antimicrobials.
Pharmacology/ Toxicology	Studies of the effects of chemicals, toxins, medicinal and nutritional factors (such as vitamins), prescription drugs, natural remedies, food components (caffeine), and potentially harmful factors (such as temperature, carbon dioxide,

	radiation) at the cellular or higher levels on plants and animals.
Physics & Astronomy	Studies of the physical properties of matter, light, acoustics, thermal properties, solar physics, astrophysics, orbital mechanics, observational astronomy, and astronomical surveys. Computer simulations of physical systems are appropriate in this category.
Plant Biology	Studies of the genetics, growth, morphology, or physiology of plants. Studies on the effects of fertilizers on plants.
Product Science (Biological)	Comparison and testing of commercial off-the-shelf products (except antimicrobials) for quality and/or effectiveness for intended use in real-world consumer-oriented applications. This category is reserved for experimental methods involving biological sciences and processes.
Product Science (Physical)	Comparison and testing of commercial off-the-shelf products for quality and/or effectiveness for intended use in real-world consumer-oriented applications. This category is reserved for experimental methods involving non-biological, physical sciences and processes.
Zoology	Studies of growth and developmental biology, anatomy, and physiology in animals other than mammals. Studies of the behavior of all animals (excluding mammals) in their natural habitats (or reproductions of them).

Table A.2: County Science Fair Sample Composition and Size

County	Year(s)	Type of Data Winners	 Participants	N
Alameda	2014 (winners only), 2015	x	x	1,020
Los Angeles	2014	x		232
San Diego	2014	x		557
San Francisco	2004-2005, 2007-2014	x		1,647
Santa Barbara	2015	x	x	113
Santa Clara	2013	x		274

CHAPTER 3 APPENDIX

Appendix 1: Immigration Trends

Earlier in the 20th century, three or four sending countries dominated immigration to the U.S. This pattern shifted to about eight to ten countries with the elimination of the National Origin Quota System.[70] Since the 1980s, China, India, and South Korea are among the top ten sending countries.[71]

There were about 100,000 Chinese immigrants in the U.S. in 1960. This number grew dramatically, reaching 3.3 million in 2010. The rapid increase in the Chinese immigrant population occurred during the 1990s, rising from the sixth largest group in 1990 to the third largest in 2000.[72] The Chinese born population is the second largest immigrant group in 2010, after Mexican immigrants, and makes up the largest ethnic group of Asian Americans.

The US Census Bureau began reporting Koreans as a distinct ethnic group in 1960 when the number of Korean immigrants was about 11,000. Korean immigration peaked in 1987, with over 35,000 immigrants to the U.S. and between 1976 and 1990, Korea was the third largest sending country. In 2000, this group of foreign born individuals reached 1 million.[73]

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[70] "The Rise of Asian American," Pew Social and Demographic Trends: Reports. Pew Research Center, 2012.

[71] Ruth Ellen Wasem, "U.S Immigration Policy Chart Book of Key Trends," Congressional Research Service, 2013

[72] Aaron Terrazas and Jeanne Batalova, Chinese Immigrants in the United States, Migration Policy Institute, http://www.migrationpolicy.org/article/chinese-immigrants-united-states-0 (May 6, 2010)

[73] Pyong Gap Min, "Koreans' immigration to the US: History and Contemporary Trends," Queens College and the Graduate Center of CUNY, 2011.

While there was only a few thousand Indian immigrants in the U.S. in the 1960s, over 300,000 Indians emigrated by the mid-1980s. More recently, the largest influx of Indian immigration occurred between 1995 and 2000. By 2011, there were nearly 2 million Indian immigrants living in the U.S. representing the third largest group of immigrants, behind Mexico and China.

Table A.2: Fertility Behavior for First-Generation Immigrants by Country of Birth, 2006-12

	Indicator for:				
Dependent Variable:	First Born Female (1)	Two Girls (2)	Mixed Sex (3)	Mixed Sex* (4)	Mixed Sex** (5)
A. First-Generation Women from China, India, or South Korea					
Has Two or More Children	0.016***				
	(0.004)				
Has Three of More Children		0.098***	-0.069***	-0.022***	-0.121***
		(0.006)	(0.004)	(0.005)	(0.005)
B. First-Generation Women from China					
Has Two or More Children	0.014*				
	(0.007)				
Has Three or More Children		0.109***	-0.091***	-0.038***	-0.148***
		(0.011)	(0.007)	(0.008)	(0.009)
C. First-Generation Women from India					
Has Two or More Children	0.020***				
	(0.006)				
Has Three or More Children		0.116***	-0.058***	-0.002	-0.118***
		(0.009)	(0.006)	(0.007)	(0.008)
D. First-Generation Women from South Korea					
Has Two or More Children	0.015				
	(0.010)				
Has Three or More Children		0.043**	-0.065***	-0.045***	-0.088***
		(0.015)	(0.010)	(0.012)	(0.013)

Notes: * p<0.05, ** p<0.01, *** p<0.001. Mixed Sex* is indicator that takes the value of 1 if the first two children are mixed sex and 0 if they are both male. Mixed Sex** takes the value of 0 if the first two born are female.

Table A.3: Male to Female Sex Ratios at Birth for First-Generation Women, 2006-2012

	All	China	India	Korea
First Child	1.06	1.06	1.04	1.10
Second Child	1.07	1.08	1.04	1.12
Conditional on female first born	1.10	1.08	1.11	1.14
Conditional on female first born & nchild=2	1.29	1.28	1.29	1.27
Conditional on male first born	1.04	1.09	1.03	1.11
Conditional on male first born & nchild=2	1.02	1.06	1.03	1.04
Third Child	1.14	1.13	1.17	1.04
Conditional on female 1st & 2nd	1.30	1.32	1.38	1.06
Conditional on female 1st & 2nd & nchild=3	1.49	1.50	1.71	1.03
Conditional on male 1st & 2nd	1.01	1.01	1.03	0.99
Conditional on male 1st & 2nd & nchild=3	0.97	0.99	0.95	0.99

Notes: Nchild refers to the number of children in the household. First- and second-generation immigrants refer to women of Chinese, Indian, or Korean ancestry. Estimates for native women are displayed for the 1990 sample. The results are consistent with the more recent data.

Table A.4: Full Interaction Results – Employed Women

Dependent Variable:	Has two or more children			Has three or more children					
Sex Composition:	First Born Female			Two Girls			Mixed Sex		
Status:	Native (1)	1st Gen (2)	2nd Gen (3)	Native (4)	1st Gen (5)	2nd Gen (6)	Native (7)	1st Gen (8)	2nd Gen (9)
Sex Composition * Status * Employed	-0.014	0.020*	-0.012	-0.007	0.023	-0.051	0.019*	-0.021*	-0.009
	(0.008)	(0.008)	(0.024)	(0.014)	(0.015)	(0.041)	(0.009	(0.01)	(0.029)
Sex Composition	0.005	-0.002	-0.002	0.077***	0	0	-0.055***	-0.056***	-0.056***
	(0.006)	(0.001)	(0.001)	(0.01)	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)
Status	0.079***	-0.086***	-0.024	0.194***	-0.211***	-0.089***	0.156***	-0.170***	-0.081***
	(0.004)	(0.004)	(0.014)	(0.007)	(0.008)	(0.023)	(0.005)	(0.006)	(0.016)
Employed	-0.038***	-0.080***	-0.080***	-0.055***	-0.119***	-0.118***	-0.050***	-0.117***	-0.117***
	(0.005)	(0.001)	(0.001)	(0.009)	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)
Status * Employed	-0.043***	0.048***	0	-0.064***	0.059***	0.04	-0.068***	0.071***	0.016
	(0.005)	(0.006)	(0.016)	(0.009)	(0.01)	(0.028)	(0.007)	(0.007)	(0.02)
Sex Composition * Status	-0.007	0.006	0.005	-0.078***	0.084***	0.014	-0.002	0	0.024
	(0.006)	(0.006)	(0.02)	(0.011)	(0.011)	(0.034)	(0.007)	(0.008)	(0.023)
Sex Composition * Employed	0.01	-0.004*	-0.004*	0.009	0.002	0.002	-0.019*	0	0
	(0.007)	(0.002)	(0.002)	(0.013)	(0.003)	(0.003)	(0.009)	(0.002)	(0.002)
Constant	0.676***	0.754***	0.767***	0.291***	0.484***	0.491***	0.338***	0.493***	0.499***
	(0.006)	(0.004)	(0.004)	(0.01)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
# Observations	1776050	1776050	1727052	559065	559065	544201	1111741	1111741	1081532

Notes: * p<0.05, ** p<0.01, *** p<0.001. Sex composition is an indicator that equals 1 if the first born child is female for Columns (1)-(3); equals 1 if the first two children are female and 0 if the first two are boys in Columns (4)-(6); or equals 1 if the first two children are mixed sex and 0 if they are the same sex in Columns (7)-(9). Status is an indicator that equals 1 if native and 0 otherwise for Columns (1), (4), and (7); equals 1 if the woman was born in China, India, or South Korea for Columns (2), (5), and (8); or equals 1 if she is a second-generation immigrant of Chinese, Indian, or South Korean descent. All regressions control for age, race, year and state fixed effects.

Table A.5: Full Interaction Results – College Education Women

Dependent Variable:	Has two or more children			Has three or more children					
Sex Composition:	First Born Female			Two Girls			Mixed Sex		
Status:									
	Native (1)	1st Gen (2)	2nd Gen (3)	Native (4)	1st Gen (5)	2nd Gen (6)	Native (7)	1st Gen (8)	2nd Gen (9)
Sex Composition * Status * College	0.018*	-0.017	-0.021	0.087***	-0.092***	0.012	-0.038***	0.044***	-0.034
	(0.009)	(0.009)	(0.029)	(0.015)	(0.017)	(0.053)	(0.011)	(0.012)	(0.037)
Sex Composition	0.029***	-0.002	-0.002	0.156***	0.009***	0.009***	-0.093***	-0.056***	-0.056***
	(0.008)	(0.001)	(0.001)	(0.013)	(0.002)	(0.002)	(0.009)	(0.001)	(0.001)
Status	-0.027***	0.036***	-0.022	0.092***	-0.103***	-0.009	0.021**	-0.022**	-0.021
	(0.005)	(0.006)	(0.019)	(0.009)	(0.010)	(0.033)	(0.006)	(0.007)	(0.024)
College	-0.065***	0.033***	0.033***	-0.099***	-0.031***	-0.031***	-0.145***	-0.036***	-0.036***
	(0.006)	(0.001)	(0.001)	(0.010)	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)
Status * College	0.098***	-0.115***	-0.008	0.069***	-0.081***	-0.056	0.110***	-0.124***	-0.051*
	(0.006)	(0.007)	(0.020)	(0.011)	(0.011)	(0.036)	(0.008)	(0.008)	(0.026)
Sex Composition * Status	-0.031***	0.032***	0.016	-0.148***	0.168***	-0.027	0.038***	-0.044***	0.047
	(0.008)	(0.008)	(0.027)	(0.013)	(0.014)	(0.048)	(0.009)	(0.010)	(0.034)
Sex Composition * College	-0.023**	-0.005**	-0.005**	-0.099***	-0.012***	-0.013***	0.037***	-0.001	-0.001
	(0.009)	(0.002)	(0.002)	(0.015)	(0.003)	(0.003)	(0.010)	(0.002)	(0.002)
Constant	0.723***	0.696***	0.709***	0.358***	0.450***	0.457***	0.442***	0.464***	0.469***
	(0.007)	(0.004)	(0.004)	(0.012)	(0.007)	(0.007)	(0.008)	(0.005)	(0.005)
# Observations	1776050	1776050	1727052	559065	559065	544201	1111741	1111741	1081532

Notes: See Table A.4 notes.

Table A.6: Full Interaction Results – Husband has Same Cultural Background

Dependent Variable:	Has two or more children			Has three or more children					
Sex Composition:	First Born Female			Two Girls			Mixed Sex		
Status:	Native (1)	1st Gen (2)	2nd Gen (3)	Native (4)	1st Gen (5)	2nd Gen (6)	Native (7)	1st Gen (8)	2nd Gen (9)
Sex Composition * Status * Intermarriage	-0.018	0.025	-0.021	-0.105***	0.074**	0.063	0.024	-0.026	-0.002
	(0.011)	(0.013)	(0.023)	(0.020)	(0.026)	(0.042)	(0.014)	(0.018)	(0.029)
Sex Composition	-0.008	-0.007*	-0.009*	-0.003	0.004	0.009	-0.046***	-0.058***	-0.057***
	(0.009)	(0.004)	(0.004)	(0.018)	(0.006)	(0.006)	(0.012)	(0.004)	(0.004)
Status	0.073***	-0.100***	-0.024*	0.107***	-0.135***	-0.061**	0.111***	-0.121***	-0.089***
	(0.007)	(0.009)	(0.011)	(0.013)	(0.017)	(0.019)	(0.009)	(0.012)	(0.013)
Intermarriage	0.024***	0.014***	0.022***	-0.062***	-0.006	0	-0.015	-0.007*	-0.004
	(0.007)	(0.003)	(0.003)	(0.013)	(0.004)	(0.005)	(0.009)	(0.003)	(0.003)
Status * Intermarriage	-0.011	0.035***	-0.011	0.053***	-0.038*	-0.004	0.003	-0.002	0.027
	(0.008)	(0.009)	(0.016)	(0.014)	(0.018)	(0.029)	(0.010)	(0.013)	(0.020)
Sex Composition * Status	0	-0.006	0.009	0.01	0.03	-0.061*	-0.013	0.014	0.016
	(0.010)	(0.013)	(0.015)	(0.019)	(0.025)	(0.027)	(0.013)	(0.017)	(0.019)
Sex Composition * Intermarriage	0.023*	0.004	0.005	0.099***	-0.003	-0.009	-0.025	-0.003	-0.003
	(0.010)	(0.004)	(0.004)	(0.019)	(0.007)	(0.007)	(0.013)	(0.005)	(0.005)
Constant	0.666***	0.737***	0.750***	0.325***	0.429***	0.432***	0.334***	0.440***	0.444***
	(0.008)	(0.005)	(0.005)	(0.015)	(0.009)	(0.009)	(0.010)	(0.006)	(0.006)
# Observations	1343472	1343472	1294474	445045	445045	430181	885213	885213	855004

Notes: See Table A.4 notes.

Table A.7: Full Interaction Results – Women in Ethnic Enclaves

Dependent Variable:	Has two or more children		Has three or more children			
Sex Composition:	First Born Female		Two Girls		Mixed Sex	
Status:	1st Gen	2nd Gen	1st Gen	2nd Gen	1st Gen	2nd Gen
	(1)	(2)	(3)	(4)	(5)	(6)
Sex Composition * Status * Ethnic Enclave	0.019	0.021	0.032	0.019	-0.003	0.012
	(0.011)	(0.032)	(0.019)	(0.059)	(0.013)	(0.040)
Sex Composition	-0.005***	-0.005***	0.001	0.001	-0.056***	-0.056***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Status	-0.047***	-0.023**	-0.158***	-0.059***	-0.112***	-0.068***
	(0.003)	(0.008)	(0.006)	(0.014)	(0.004)	(0.010)
Ethnic Enclave	-0.008*	-0.013***	-0.011	-0.014*	-0.018***	-0.020***
	(0.004)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Status * Ethnic Enclave	0.001	0.005	-0.023	-0.011	-0.006	0
	(0.007)	(0.022)	(0.013)	(0.040)	(0.009)	(0.029)
Sex Composition * Status	0.013**	-0.006	0.093***	-0.022	-0.012*	0.017
	(0.005)	(0.012)	(0.008)	(0.021)	(0.006)	(0.015)
Sex Composition * Ethnic Enclave	0.004	0.004	-0.015	-0.012	0	-0.002
	(0.005)	(0.005)	(0.009)	(0.009)	(0.006)	(0.006)
Constant	0.715***	0.728***	0.438***	0.446***	0.448***	0.454***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.005)
# Observations	1776050	1727052	559065	544201	1111741	1081532

Notes: See Table A.4 notes.