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Edward Kim
Bentley University

Joshua Goodman
Boston University and IZA

Martin R. West
Harvard University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Kumon In: The Recent, Rapid Rise of Private Tutoring Centers

The increasing prevalence of private tutoring has received minimal scholarly attention in the United States. We use over 25 years of geocoded data on the universe of U.S. private tutoring centers to estimate the size and growth of this industry and to identify predictors of tutoring center locations. We document four important facts. First, from 1997 to 2022, the number of private tutoring centers more than tripled, from about 3,000 to 10,000, with steady growth through 2015 before a more recent plateau. Second, the number and growth of private tutoring centers is heavily concentrated in geographic areas with high income and parental education. More than half of tutoring centers are in areas in the top quintile of income. Third, even conditional on income and parental education, private tutoring centers tend to locate in areas with many Asian American families, suggesting important differences by ethnic or cultural identity in demand for such services. Fourth, we see only marginal evidence that prevalence of private tutoring centers is related to the structure of K-12 school markets, including the prevalence of private schools and charter or magnet school options. The rapid rise in high-income families' demand for this form of private educational investment mimics phenomena observed in other spheres of education and family life, with potentially important implications for inequality in student outcomes.

Keywords: education, tutoring

Corresponding author:
Joshua Goodman
Boston University
Commonwealth Ave
Boston, MA 02215
USA

E-mail: edecjosh@bu.edu

1. Introduction

Tutoring has recently gained substantial attention in education policy discussions. In the wake of the COVID-19 pandemic, many policymakers and schools have turned toward various forms of tutoring as one potential way to address the disruptions that interfered with student learning and widened achievement gaps by income and race. The focus on tutoring is driven by fairly extensive evidence of its positive impacts on learning, both overall and for those with low socioeconomic status (Nickow et al., 2023; Dietrichson et al., 2017). In 2024, the Biden Administration made provision of high-dosage tutoring one of the three pillars of its Improving Student Achievement Agenda. The tutoring centered in these recent policy discussions is publicly funded and provided in school buildings.

Private tutoring has, in contrast, received substantially less attention, even as it has grown increasingly popular across the world in recent decades (Bray, 2010; Bray & Lykins, 2012). National surveys suggest the United States is no exception to this pattern. In 1992, 10 percent of high school seniors reported taking a private class to prepare for the SAT.[1] That number quadrupled by 2012, with 40 percent reportedly taking a course to prepare for a college admissions exam.[2] In 2022, approximately 6-7% of US families with children between ages 6 and 17 had paid for tutoring in the past year, paying an average of about \$437 in months with such a purchase. The top 10% and 5% of reported monthly spending were respectively closer to \$1,200 and \$2,000.[3] Private tutoring could theoretically reduce or increase inequality in student outcomes, depending

[1] Authors' calculations based on the 1992 wave of the National Education Longitudinal Study.
[2] Authors' calculations based on the 2012 wave of the High School Longitudinal Study.
[3] Authors' calculations based on the Consumer Expenditure Survey.

on which students receive such services. Understanding the distributional impacts of private tutoring requires better knowledge of who is being served by the industry.

This paper focuses on the private tutoring industry, defined as "tutoring in an academic school subject, which is taught in addition to mainstream schooling for financial gain" (Bray and Silova, 2006). As a supplementary resource, private tutoring occupies a different role in the education marketplace than private schools, which are full substitutes for mainstream schooling. Families can combine private tutoring with any schooling arrangement, whether private or public. Though informal arrangements such as hiring a neighborhood teenager qualify as private tutoring, research suggests the growing popularity of private tutoring is due to the rise of larger scale private tutoring firms (Aurini, 2004). Such firms run physical locations outside of schools called tutoring centers, which students attend to receive services, often in small groups. Lessons can focus on mainstream school curricula or standardized exam content, and tutors differ widely in age and qualifications (Bray & Silova, 2006). Some private tutoring firms run single locations while others are large national chains, such as Kumon, Sylvan, and Huntington Learning Centers.

In this paper, we use over 25 years of geocoded data on the universe of U.S. private tutoring centers to measure the size and growth of this industry, as well as to explore the economic and demographic predictors of tutoring center locations. We document four important facts. First, from 1997 to 2022, the number of private tutoring centers more than tripled, from about 3,000 to 10,000, with steady growth through 2015 before a plateau through 2022. Second, the number and growth of private tutoring centers is heavily concentrated in geographic areas with high incomes and high levels of parental education. As of 2020, 60 percent of tutoring centers were in areas representing the top fifth of the income distribution, and nearly same percent of tutoring centers that newly opened between 2000 and 2020 opened in such areas. Third, even conditional on income and educational attainment, private tutoring centers tend to locate in areas with many Asian American families, suggesting important differences by ethnic or cultural identity in demand for their services. Fourth, we see only marginal evidence that the prevalence of private tutoring centers is related to the structure of K-12 school markets, including the prevalence of private schools and charter or magnet school options.

Our work contributes to three strands of the research literature. First, and most broadly, our work documents a rapid rise in high-income families' demand for private education investments that mimics phenomena observed in other spheres of family life. High-income families are increasing their investments in early childcare (Ramey and Ramey, 2010), parental time spent with children (Guryan, Hearst and Kearny, 2008), and extracurricular activities (Levey Friedman, 2013), while viewing kindergarten increasingly as a time for academic focus rather than play and socializing (Bassok, Latham and Rorem, 2016). Such families are also demanding more intensive and competitive secondary education, pushing for dual enrollment programs, Advanced Placement classes, and International Baccalaureate programs (Davies & Hammack, 2005). This increased competition and pressure among high-ability students leads them to search for ways to maximize their chances for success, including the use of private tutoring (Bound, Hershbein, & Long, 2009), which does seem to moderately increase SAT scores and rates of selective college enrollment (Buchmann, Condron, and Roscigno, 2010). Such increasing parental investment in children appears both in the U.S. and in international data (Doepke et al., 2019).

Second, empirical research on private tutoring enrollment in the United States is limited, with notable exceptions documenting its prevalence among Asian American immigrants and communities (Byun & Park, 2012; Lee & Zhou, 2014; Zhou & Kim, 2006). Studies of its effects on participating students have focused on the approximately 2,000 firms that were approved to provide supplemental educational services under the federal No Child Left Behind Act; a meta-analysis of twenty-eight evaluations of such providers documented an overall small positive effect on state test scores with considerable heterogeneity (Ascher, 2006; Chappell et al., 2011). However, this NCLB policy targeted low-income students in underperforming schools, a very different population than those served by the typical private tutoring center. While the effectiveness of one-on-one or very small group tutoring is well documented (Cohen, Tulik, & Tulik, 1982; Wasik & Slavin, 1993; Fryer, 2014; Kraft, 2014), we have little evidence on the effectiveness of the specific forms of tutoring offered by these centers. We also know little about which students and families have demand for these services, something our descriptive evidence attempts to remedy.

Third, our findings help place the U.S. private tutoring industry into a broader international context. Some characteristics, such as a tight linkage with consequential exam systems, are common to private tutoring industries across the world, but each country's context can shape the industry significantly (Bray & Silova, 2006). In South Korea, although upper-income families exhibit the greatest demand for private tutoring, the practice is widespread (Kim & Park, 2010). Household expenditures on private tutoring rival government spending on primary and secondary schooling, perhaps because homogenization of secondary school quality and a hierarchical higher education system drive students to use private tutoring to distinguish themselves for college admission processes (Kim & Lee, 2001; Kim & Lee, 2010). Research also suggests that demand for private tutoring in South Korea is greater in areas with lower local school quality and fewer school choice options (Kim, 2004; Kim & Lee, 2010).

In Canada, private tutoring serves primarily as a financial middle ground for families who are dissatisfied with their public schooling options but cannot afford the tuition of private schools (Davies, 2004). With neither university entrance exams nor a strict hierarchy of university prestige, the Canadian private tutoring industry advertises itself in response to perceived shortcomings of public schools, emphasizing small class sizes, personalized curricula, and individual attention (Aurini, 2004; Aurini & Davies, 2004). Middle-income families appear to be the target market for private tutoring, as upper-income families dissatisfied with public school options can afford private schools, while for lower-income families private tutoring may be unaffordable. As in South Korea, demand is tied to desire among families dissatisfied with mainstream schooling to provide additional educational resources to their children. However, the type of family associated with that dissatisfaction differs between the two countries.

Our results suggest that private tutoring centers in the U.S. are closer to the South Korean model in targeting high-income families, though they are not (yet) nearly as widespread as in that country. Like South Korea, the U.S. has a hierarchical higher education system with intense competition for admission to the most elite institutions. The prevalence and growth in tutoring centers we document may be related to the perception by U.S. parents of the high stakes associated with their children's educational achievement given this postsecondary landscape.

2. Data

We combine multiple data sets to conduct our investigation. Measures of private tutoring center prevalence come from Data Axle's Historical Business Data, which collects information on the physical location of businesses sourced and verified by yellow page directories, credit card billing data, phone verification, web research, news publications, and annual reports. Data collection began in 1997 and has continued annually through 2022, the most recent year available. Each business included in the data represents a different physical location, with identifiers that allow the business to be tracked across years. We observe businesses' names, addresses, and industry codes, as well as some measures of size.

We identify businesses registered as either "Tutoring" (SIC Code 829909) or "Test Preparation Instruction" (SIC Code 874868), ultimately finding about 24,000 unique firms with approximately 33,000 locations across all years. "Tutoring" firms are 40 times more numerous than "Test Preparation Services" firms. Some franchises have branches in both categories, however, so we combine them for our primary outcome measure. We then combine the tutoring center location data with school district boundary files to locate tutoring centers within school districts. We successfully match 99.6 percent of our business observations to a school district, with the remainder either missing location data or existing outside a school district boundary.

We use the federal government's Common Core of Data (CCD) from 2000-01 to 2020-21 to generate school- and district-level data on public schools and districts. We use the school-level data to calculate, for each school district, enrollment in charter and magnet schools, counts of free or reduced-price lunch (FRPL) and a segregation metric (dissimilarity index) we calculate from FRPL across schools in the districts. At the district level we use the ratio of students to various staff (e.g., student-to-teacher, student-to-administrator), fiscal data, grades offered, and urbanicity designation (i.e., rural, town, suburb, or urban).

We merge community-wide demographic information at the school-district level from the 2000 U.S. census and American Community Survey (ACS) five-year data sets spanning 2015-2020 for elementary, secondary, and unified school districts. Variables we draw from the census and the ACS include per capita income, proportion of adults with at least a bachelor's degree, proportion of individuals foreign born, and number of children enrolled in private or public school.

We define our main outcome variable, tutoring centers per 1,000 students, based on student totals from the census and ACS, rather than the CCD, as the former capture student enrollment in both public and private school. After aggregating all data sources, our final analytic data set includes approximately 13,000 unique school districts.

3. Methods

We perform three sets of analyses. First, we document the rise in tutoring center prevalence over time and by location, with the goal of understanding the magnitude and geographic spread of this phenomenon. We believe this is the first analysis to measure how many tutoring centers exist, where they locate, and how this has changed over time.

Second, we identify school-district-level covariates related to private tutoring based on prior literature and a machine learning approach. Existing research suggests a number of potentially important correlates of tutoring center prevalence and growth, including: income (Lee, 2005; Tansel & Bircan, 2006), income inequality (Dang & Rogers, 2008; Atalmis, Yilmaz, & Saatcioglu 2016), racial demography (Byun & Park, 2012; Bray & Lykins, 2012; Shin, 2012), immigration status (Sriprakash, Proctor, & Hu, 2016), school quality (Kim, 2004), and availability of school choice (Kim & Lee, 2001; Kim & Lee 2010). We also look to literature on private school openings and prevalence for more possible correlates, given the theoretical overlap between school choice and private tutoring, and found similar ideas as well as some unique suggestions such as age demography (Barrow, 2006) and total population size (Downes & Greenstein, 1996).

A purely theory-driven approach to selecting variables for our final models may overlook potential covariates unique to the United States setting, and the high correlation between many of predictors would render a model with all of them impossible to interpret sensibly. Instead, we employ the LASSO (Least Absolute Shrinkage and Selection Operator) variable selection method to guide our choices. LASSO uses within-sample cross-validation to identify a set of predictors that explains the most variation in the outcome subject to a penalty for overfitting (Tibshirani, 1996). From a pool of more than 50 candidate covariates, we identified 4 that performed well across both model specifications and captured overall patterns.

We run our LASSO procedure on two linear models. We first ask what community-level characteristics predict the prevalence of tutoring centers at a given moment in time. Our first model focuses on 2020, the most recent year with available predictor data. We estimate:

$$\text{Tutoring}_{d,2020} = \beta_0 + \beta_X \times X_{d,2020} + \epsilon_d \tag{1}$$

where the outcome is school district *d*'s number of tutoring centers per 1,000 school-age children in 2020 and *X* represents a vector of district-level demographic and economic characteristics. The coefficients β_X estimate the association between such characteristics and tutoring center prevalence, demonstrating which contemporaneous variables most strongly predict tutoring center location.[4]

[4] The results generated by using data from the most recent year (2020) are quite similar to those using earlier years of data, so we omit the latter for simplicity.

We then ask how community-level characteristics have predicted the change in tutoring center prevalence over time. Our second model predicts that change in prevalence between 2000 and 2020, the earliest and latest years for which we can observe most all potential predictors. We formulate this equivalently to Equation (1) but substitute the change between 2000 and 2020 for the outcome and all covariates:

$$\Delta \text{Tutoring}_{d,2020-2000} = \beta_0 + \beta_X \times \Delta X_{d,2020-2000} + \epsilon_d \tag{2}$$

For both models, we restrict the sample to districts serving over 100 students in the year 2020 to avoid outlier values, as many covariates use students served as a denominator. In the next section, we describe in more details the variables identified as strong predictors by the LASSO procedure.

Finally, we ask whether the most important predictors of tutoring center prevalence and change exhibit non-linearities in their predictive power. To do so, our third set of analyses utilize the predictors identified by the LASSO procedure in a non-parametric regression model, again separately specifying for concurrent prevalence and change over time:

$$\text{Tutoring}_{d,2020} = \beta_0 + \sum_{i=1}^{20} \beta_{X,i}^{T} \times \boldsymbol{I}_{X,i}\left(X_{d,2020}\right) + \epsilon_d \tag{3}$$

$$\Delta \text{Tutoring}_{d} = \beta_0 + \sum_{i=1}^{20} \beta_{X,\imath}^{\ddot{T}} \times \boldsymbol{I}_{\Delta X,i}(\Delta X_d) + \epsilon_d \tag{4}$$

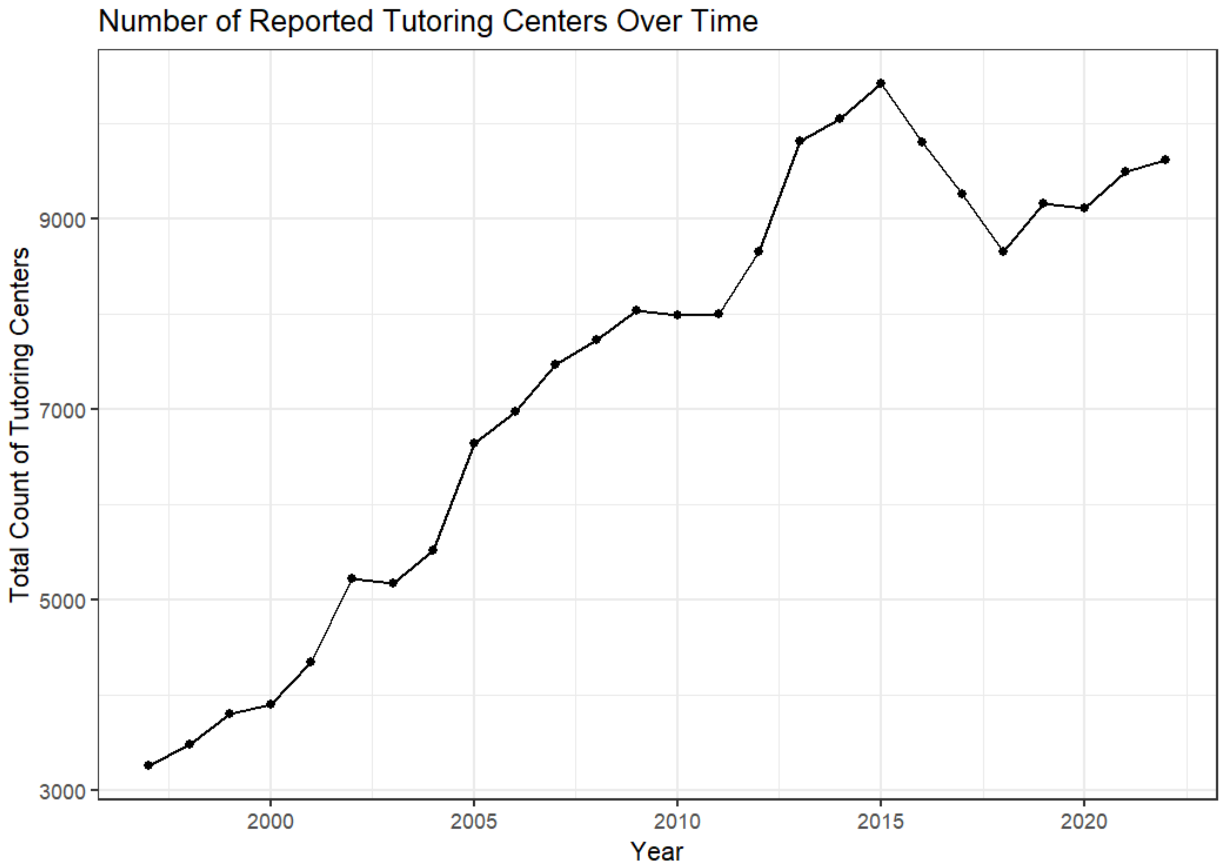
In Equation (2), $\boldsymbol{I}_{X,i}\left(X_{d,2020}\right)$ is a vector of indicators for whether school district *d* in the year 2020 was in the *i*th vigintile for each covariate in the set of variables *X*. In Equation (3), ΔX_d gives the change in the covariate for unit *d* between 2000 and 2020, and $\boldsymbol{I}_{\Delta X,i}(\Delta X_d)$ is defined similarly as the previous model. This specification allows us to study the relationship between tutoring center prevalence and the entire distribution of various predictors, rather than imposing a strictly linear specification. As with the previous set of analyses, we similarly restrict our regression models to the sample of districts serving over 100 students in the year 2020.

4. Results

4.1 Tutoring Center Growth and Geographic Spread

The number of private tutoring centers in the U.S. roughly tripled between 1997 and 2022, as seen in Figure 1. In 1997, there were just over 3,000 private tutoring centers in the United States, and until 2015, that number increased steadily and roughly linearly over time, averaging 6.8% growth each year. Industry growth, as measured by number of firms, then declined until 2018, and then steadily rose again, with total firms numbering close to 10,000 in 2022.

Figure 1: Private tutoring industry growth over time



Large chains, such as Kumon and Sylvan, make up a substantial portion of these tutoring centers. Table 1 shows the top 10 tutoring center chains as measured by total number of unique locations across all years in our data. Those top 10 chains account for nearly 10,000 different locations over time, or 30% of all tutoring centers observed. In 2022, the top 10 chains had over 4,100 locations, or 43% of the centers that year. The largest chain, Kumon, had nearly 1,900 locations in 2022, accounting for nearly 20% of all tutoring centers in the United States that year. The next most prevalent chains in 2022, Mathnasium and Sylvan, each were about one-third the size of Kumon, with just over 600 locations. Even with such large chains, 57% of tutoring centers in 2022 were either single location firms or smaller tutoring chains.

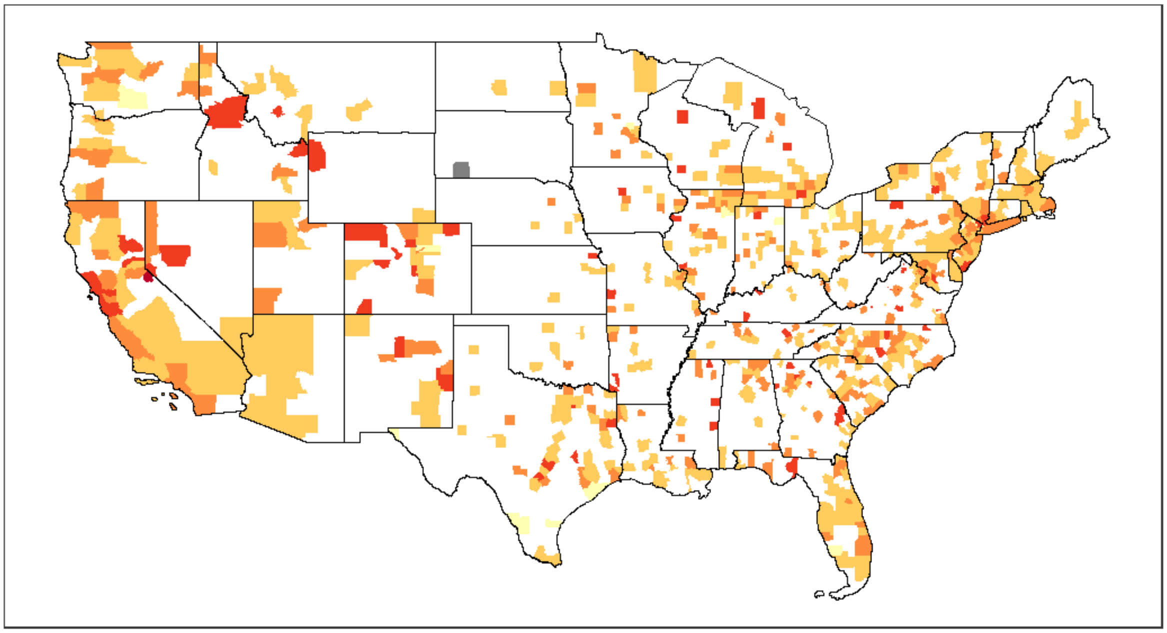
Table 1: Top 10 Tutoring Chains

Company	Unique locations from 1997-2022	Unique locations in 2022
Kumon	3,483	1,890
Sylvan	2,286	605
Club Z	972	182
Huntington	946	360
Mathnasium	922	619
Tutor Doctor	334	182
Eye Level	329	218
Kaplan	290	23
Tutoring Club	272	70
Princeton	163	8
Total of top 10	9,997	4,157
All centers	33,396	9,622

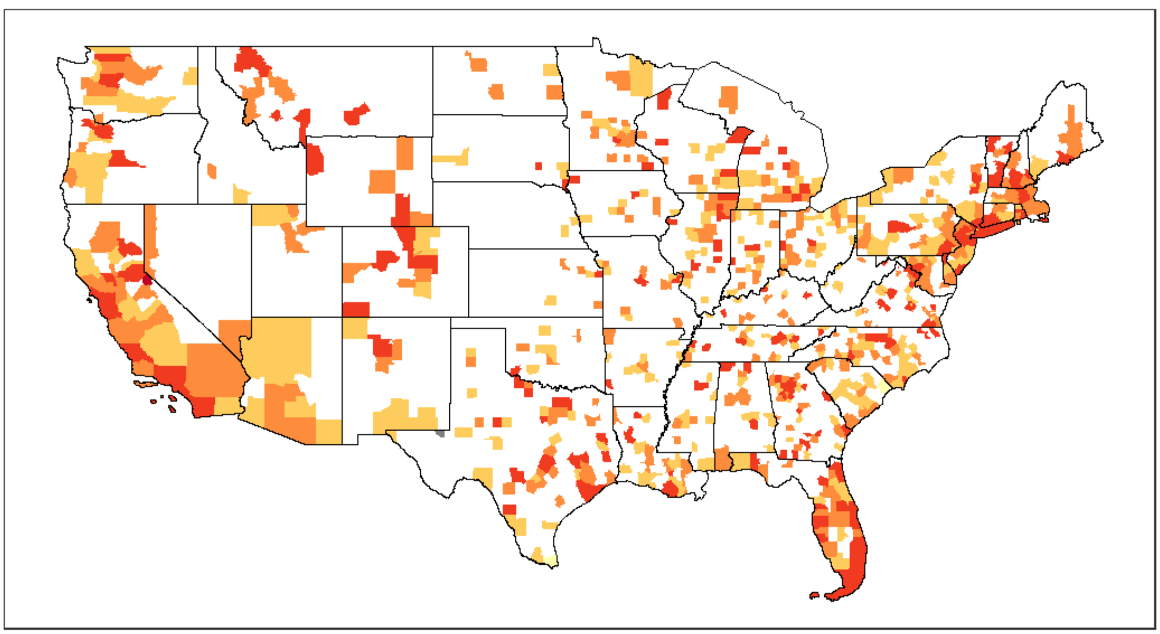
Tutoring centers are more prevalent on the East and West coasts of the U.S., but growth over time has occurred throughout the country. Figure 2 shows the number of tutoring centers per school-age child by county in both 2000 (panel A) and 2020 (panel B). Though most counties still have no tutoring centers, the industry has both expanded to new areas of the country and become more densely concentrated. Table 2 shows that the percent of counties without any tutoring centers decreased from 77.8% to 74.0% from 2000 to 2020. The share of counties with some tutoring centers but ratios less than 1:10,000 also decreased during this period, from 13.0% to 9.0%. Meanwhile, the share of counties with ratios of at least 1:5,000 nearly tripled from 2.6% to 7.5%.

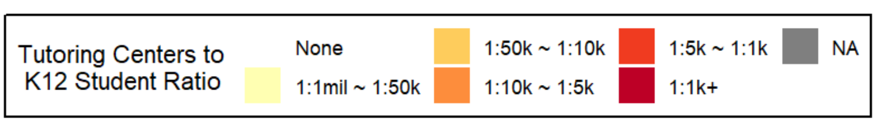
Figure 2: Tutoring center to K-12 student ratio by county in 2000 and 2020.

(A) Tutoring Prevalence, 2000



(B) Tutoring Prevalence, 2020





This pattern of greater prevalence and greater density is evident for all four major regions of the United States but is most pronounced for the Northeast: between 2000 and 2020 the percent of counties in that region without any tutoring centers dropped by 7.2 percentage points, while the percent of counties with a ratio greater than 1:1,000 increased nearly tenfold from 2.3% to 19.6%.

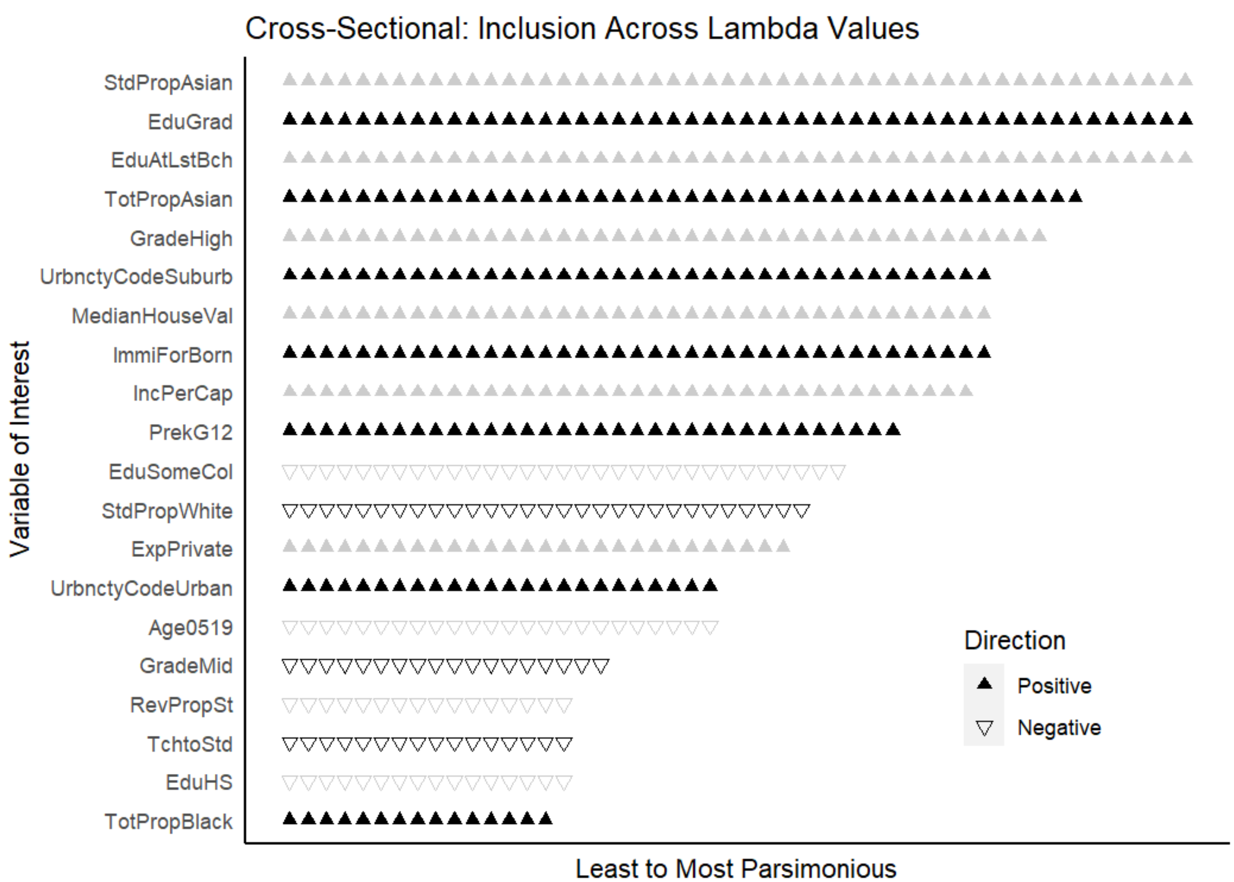
Table 2: Proportion of counties with given tutoring center to K-12 student ratios

2000 Percent 2020 Percent	None	1:1mil - 1:50k	1:50k - 1:10k	1:10k - 1:5k	1:5k - 1:1k	1:1k +
Overall	77.9%	0.5%	12.5%	6.5%	2.5%	0.1%
	74.0%	0.1%	8.9%	9.5%	7.4%	0.1%
Northeast	49.6%	0.9%	33.2%	14.1%	2.3%	0.0%
	42.3%	0.0%	17.7%	20.5%	19.6%	0.0%
South	79.2%	0.4%	10.9%	6.8%	2.5%	0.2%
	74.1%	0.1%	8.8%	8.7%	8.2%	0.1%
Midwest	85.4%	0.3%	9.6%	3.5%	1.1%	0.0%
	82.7%	0.1%	7.0%	7.2%	3.0%	0.0%
West	69.6%	0.5%	14.1%	9.0%	6.1%	0.2%
	68.4%	0.0%	9.4%	12.3%	9.7%	0.2%

4.2 Choosing Predictors

We employed a LASSO procedure to guide our investigation of associations between school-district characteristics and private tutoring. Based on the models specified earlier, LASSO identifies an optimal combination of predictors from a set of variables by balancing predictive accuracy against model parsimony. We began with over 50 variables describing wealth, education, age, race and ethnicity, immigration, mobility, occupation, family structure, school and district staff, and district fiscal information. The full list of candidate variables appears in Appendix A.

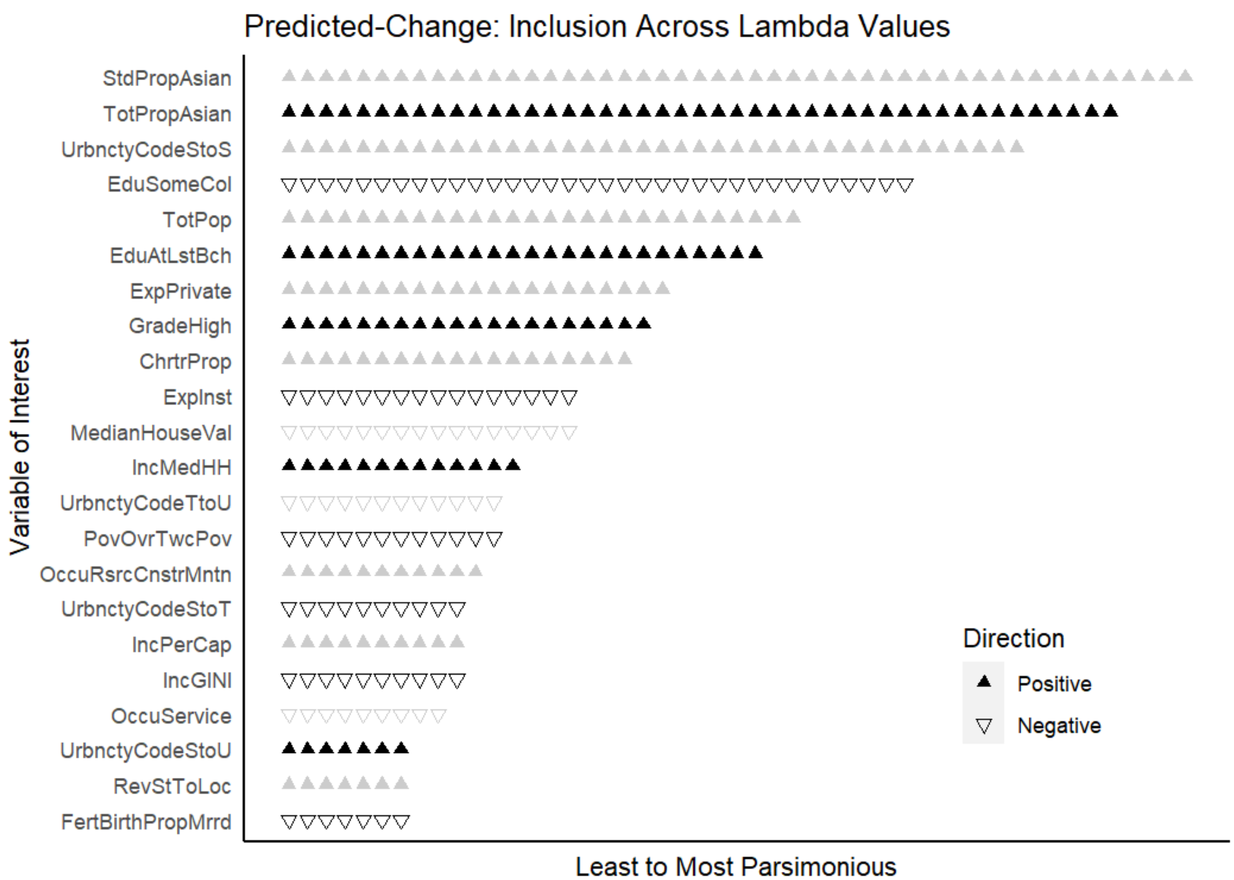
Figure 3: Covariates Included by LASSO, Cross-Sectional Model



Note: Inclusion of covariates in the cross-sectional model across tuning parameter values, from "optimal" to one standard error away from optimal. Each arrow indicates inclusion in the model at that level of parsimony and the direction of the association.

The LASSO procedure results in Figures (3) and (4) suggest a few prominent themes associated with tutoring center prevalence. Most noticeable, appearing across multiple variables at the highest levels of model parsimony in both the cross-sectional and predicted-change model, were variables related to Asian American identity, followed closely by those related to educational attainment. The procedure also consistently identified wealth, as captured by median household income, median home value, and/or per capita income. Also notable were variables related to urbanicity, particularly suburban classification, and whether a district offered high school. School choice related variables demonstrated a more distal and inconsistent showing, a point which we address below. No other themes could be consistently identified across both models.

Figure 4: Covariates Included by LASSO, Predicted Change Model



Note: Inclusion of covariates in the predicted change model across tuning parameter values, from "optimal" to one standard error away from optimal. Each arrow indicates inclusion in the model at that level of parsimony and the direction of the association.

Based on these results, we select three covariates for our main regression models: (1) proportion Asian student population, (2) proportion of the population with at least a bachelor's degree, and (3) income per capita. These covariates best captured their associated theme, and we deliberately avoided repeating domains (e.g., proportion with at least a bachelor's degree versus proportion with a graduate degree) especially given that exploratory analysis revealed the LASSO procedure would use similar variables interchangeably if one were excluded.

We further include a fourth covariate: (4) proportion private school enrollment. Theory and prior research have consistently suggested a relationship between school choice and private tutoring. Charter school student enrollment and public school district expenditures on private schools (as reported by the CCD) did feature somewhat in the LASSO procedure, particularly in the predicted-change model. However, further investigation revealed that these variables both had very skewed distributions, which encourages linear models to mistake high influence points for high signal. To be thorough in our analysis, and relate our findings to this prior literature, we add to our models the proportion of K-12 students enrolled in private school which, while still related to school choice, had a more even distribution and consistent relationship with private tutoring.

To preserve the scope of our analysis, we do not include in our models the covariates related to urbanicity nor whether high school grades were offered in the school district. Note that their inclusion as additional controls did not substantively change any of the model results we present in the sections below, though their prominence in the LASSO results, not to mention all the other covariates we exclude from this investigation, would suggest promising future investigations.

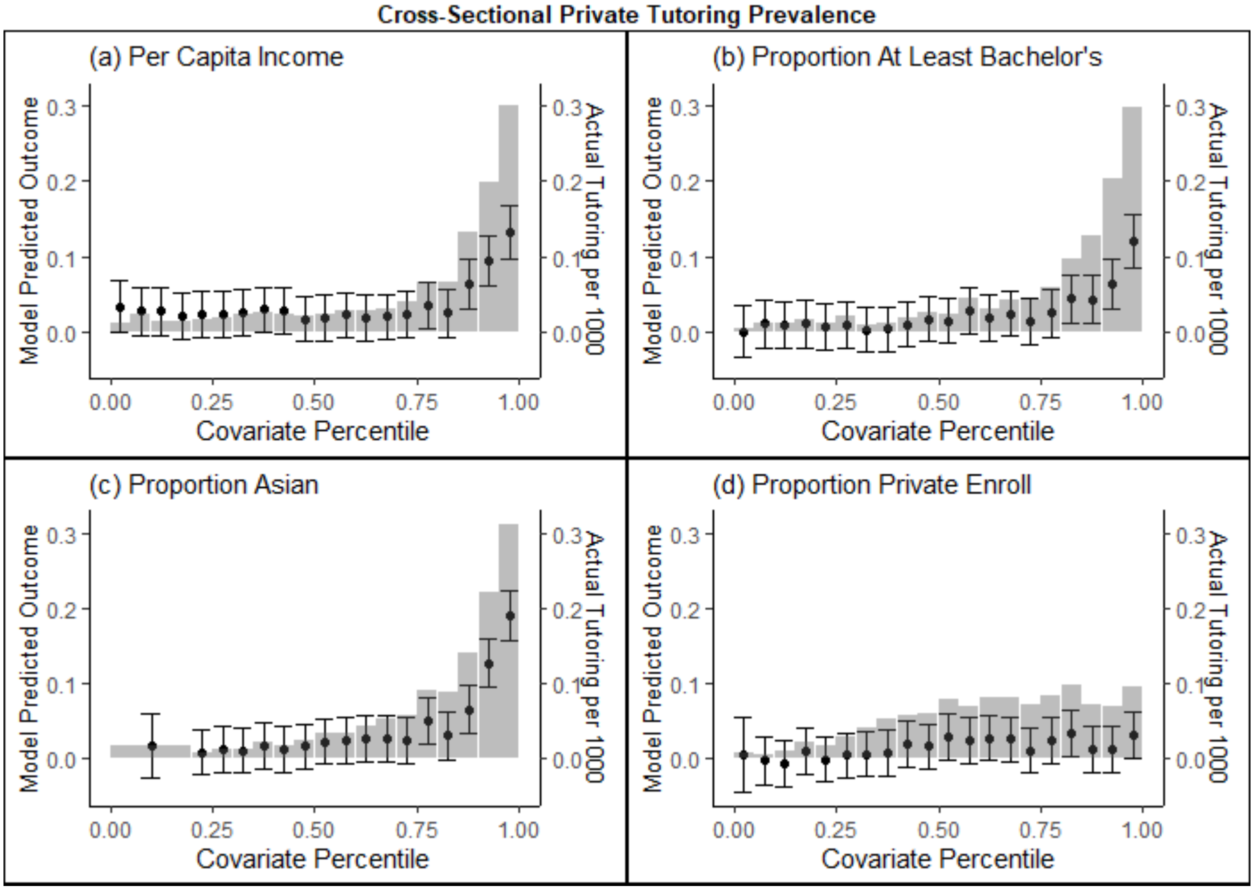
4.3 Non-Linearities in Predictors of Tutoring Center Prevalence and Growth

Tutoring centers are much more prevalent in the top 15-20% of school districts as measured by income, education, and fraction of Asian American families. Figure 5 displays the fully controlled model results of model (3), alongside the actual tutoring prevalence across the distributions of each covariate. When controlling for other covariates, most vigintiles are roughly equivalent to the reference category, with only the highest few showing sharp differences. This suggests private tutoring exists mostly at the extremes, corroborating the geographic results the previous section showing clusters of prevalence. The R^2 from this model is about 0.2, suggesting that the included covariates statistically explain about 20 percent of the variation in tutoring center prevalence.

Changes in tutoring center prevalence are predicted most sharply in areas whose Asian American population grew the most. Figure 6 displays the fully controlled model results of the predicted change model (4). For the predicted change model, school districts that experienced the greatest increase proportion Asian student body also witnessed the most growth in private tutoring prevalence. Changes in income, education and private school enrollment show less variation, with the latter arguably demonstrating a slight negative association. Important to note is that the percentile bins are not evenly spaced across the covariate's distribution: the difference in per capita income between the 19^{th} and 20^{th} bins in the cross-sectional model is about \$22,000, while the same for the 1^{st} and 2^{nd} bins is about \$4,000. The R^2 from this model is about 0.03, suggesting that changes over time in the included covariates statistically explain about 3 percent of the change over time in tutoring center prevalence.

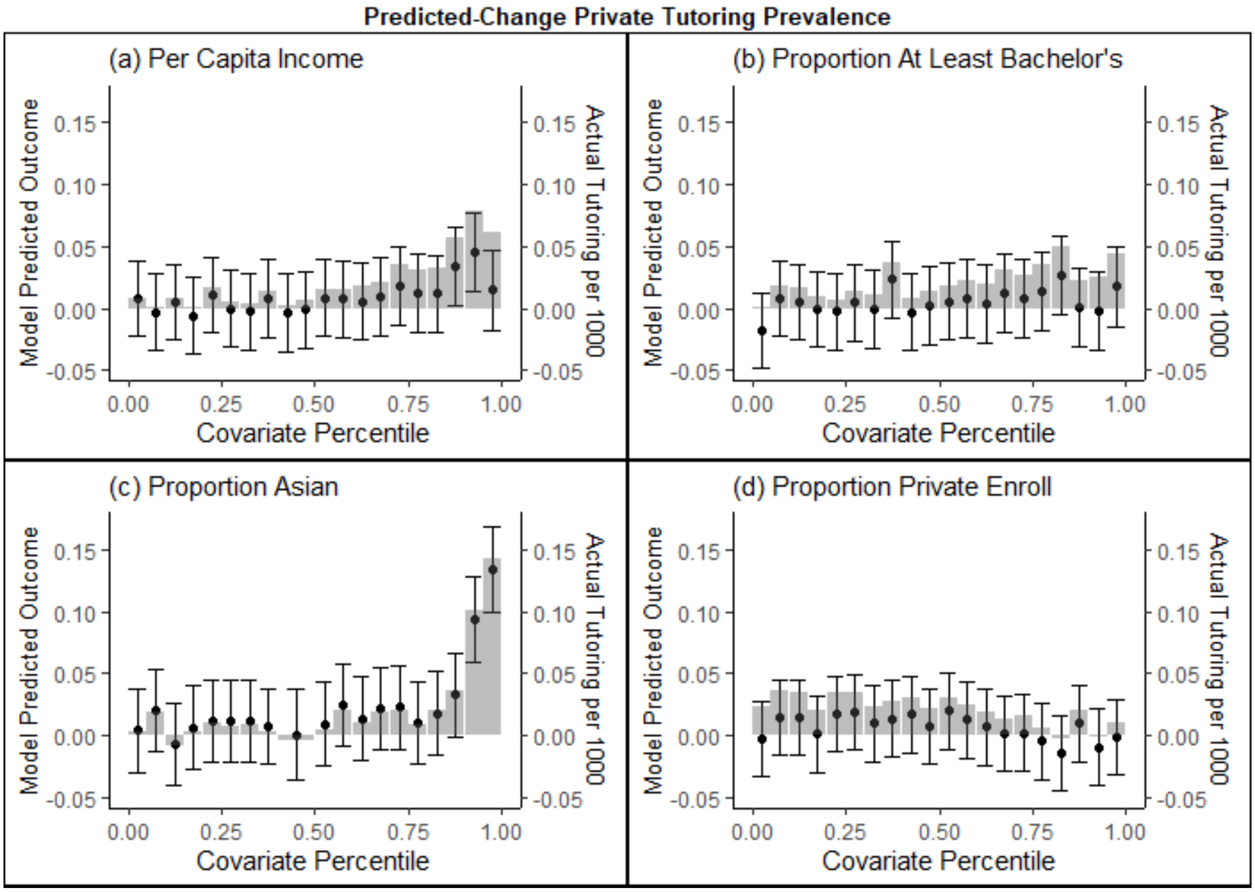
We further unpack the exact relationship between each predictor and private tutoring prevalence in each of the following subsections.

Figure 5: Non-Linearities in Tutoring Center Prevalence, Cross-Sectional Model



Notes: Non-parametric model results for the cross-sectional model. Point estimates give the predicted outcome value for the covariate of interest set to the given vigintile, and all other covariates set to the bin containing the median. Note the leftmost bin for proportion Asian represents 20% of the data, a result of uniformity on the left-hand side of the distribution.

Figure 6: Non-Linearities in Tutoring Center Prevalence, Predicted Change Model

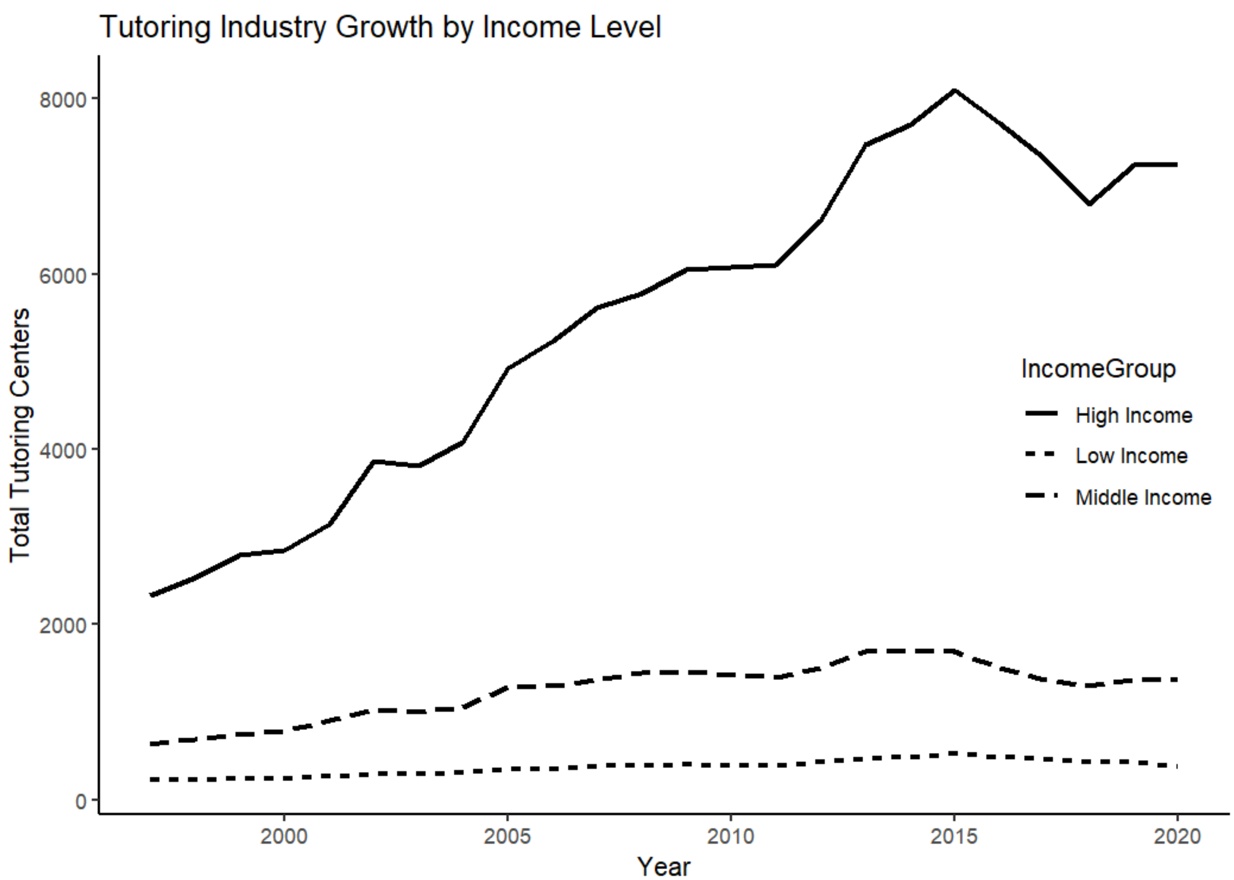


Notes: Non-parametric model results for the predicted change model. Point estimates give the predicted outcome value for the covariate of interest set to the given vigintile, and all other covariates set to the bin containing 0 (no change).

Income

Figure 5 shows an overall positive association, in both the cross-sectional and predicted change model, between income per capita and private tutoring prevalence. Controlling for other covariates, on average a school district in the highest vigintile of per capita income in 2020 (at least $57,000) had 0.133 tutoring centers per 1000 students, whereas the median district in 2020 (between $29,000 and $30,000) had 0.017 tutoring centers per 1000. Districts which displayed the second highest vigintile of per capita income change between 2000 and 2020 saw 0.045 more tutoring prevalence in that same period (notably, the highest vigintile shows near zero change). This pattern of disparate growth is corroborated by Figure 7, which displays tutoring per 1000 students for school districts with top- middle- and bottom-third per capita income in 2020. A disproportionate amount of the overall growth took place in the highest income brackets, with the lower income group showing minimal growth.

Figure 7: Tutoring center growth by school district income



Notes: School district income is measured in 2020 and divided into terciles.

To the extent that private tutoring demand is driven by a dissatisfaction with the educational resources offered in mainstream schooling, the large degree of segregation by income across U.S. school systems (Bischoff & Reardon, 2014) would suggest that high-income families would be the least interested in private tutoring, as their children arguably already receive the best educational experience (e.g., well-funded schools through local tax revenue, access to high social capital networks, etc.). Our descriptive results suggest this is not the case. Private tutoring is disproportionately concentrated in higher income school districts and higher income families seem the most interested in private tutoring.

Bound, Hershbein, and Long (2019) offer a potential explanation: the highest performing and most advantaged students perceive the most pressure to succeed due to increasingly intense competition, and, as one response, turn towards private tutoring to supplement their educational resources. To maximize educational resources, high-income families would enroll in private tutoring in addition to high-quality mainstream schooling, which offers a similar experience to one's peers and therefore one's immediate competition. Future investigations could empirically confirm the direct relationship between interest in private tutoring and relative economic standing among immediate peers.

Educational Attainment

The patterns in Figures 5 and 6, depicting the outcome across proportion of population over 25 with at least a bachelor's degree, resemble a somewhat less consistent version of the same for per capita income: the cross-sectional figure shows a clear, upward trend towards higher ends of the spectrum; the predicted-change figure is less consistent and suggests a more even trend. But the relationship between private tutoring prevalence and educational attainment is not merely a proxy for an association with income. Recall our models control for per capita income, and the

LASSO procedure evidently identified educational attainment, not wealth, as the more important predictor of private tutoring prevalence in the United States.

The relationship between private tutoring enrollment and parent educational attainment levels appears consistently positive across research settings (Tansel & Bircan, 2006; Nath, 2008; Kim & Park, 2010; Zhang & Xie, 2016). Part of this observed effect is likely due to the high coincidence between educational attainment and income, the latter being a prerequisite for private tutoring enrollment. But parent educational attainment may additionally reflect higher parental expectations of children (Bray & Kwok, 2003), and children reared in communities of well-educated adults may pursue similar outcomes via transmission of cultural capital (Lareau, 2001).

Asian American Population

Previous studies have looked at the relationship between private tutoring and racial/ethnic groups in the United States, particularly for Asian Americans (Shrake, 2010), and some have even suggested private tutoring as an explanation for Asian American communities' exceptional academic performance (Byun & Park, 2012; Zhou & Kim, 2006). We build on these observations by considering demographic composition with respect to proportion Asian American which was identified as the most relevant covariate in the LASSO procedure, even appearing twice via proportion student population *on top of* proportion general population.

The proportion of Asian American students was identified as an important predictor by the LASSO procedure at every level of parsimony and demonstrates some of the largest coefficients in the nonparametric regression model. School districts with the highest concentrations of Asian American students in 2020 had 0.31 tutoring centers per 1000 compared to 0.02 for districts with few Asian American students. Changes in Asian American prevalence appears more relevant than changes in income or education levels for predicting change in tutoring prevalence.

Based on relevant research documenting the behavior of Asian American communities toward schooling in the U.S., we posit some portion of the observed relationship comes from a cultural familiarity with private tutoring in families' countries of origin. Research conducted in common countries of origin for Asian Americans reports substantial amounts of private tutoring, for example: China (Kwok, 2010), India (Bhorkar & Bray, 2018), Philippines (de Castro & de Guzman, 2014), Vietnam (Dang, 2007) and South Korea (Kim & Lee, 2002). Immigrant parents in the United States, particularly those of Asian origin, are also relatively optimistic and hold high expectations of their children with regard to educational opportunities (Duong, Badaly, & Liu, 2016, Kao & Tienda, 1995, Schneider & Lee, 1990; Goyette & Xie, 1999; Raleigh & Kao, 2010), a perspective which could encourage interest in supplemental educational resources. However, Sriprakash, Proctor, and Hu (2016), in their study of Chinese immigrants in Australia, warn against essentializing these communities' demand for private tutoring as a cultural phenomenon. They suggest that private tutoring enrollment can instead be understood as a "considered, strategic response" from families with disposable income, but less social and cultural capital, to education systems that heavily weigh exam results while minimally tailoring curricula to exam preparation. While our investigation cannot confirm this theory, the factors that Sriprakash, Proctor, and Hu (2016) describe in the Australian context seem present in the U.S. context, too.

School Choice

The theoretical connection between private tutoring and school choice consists of multiple facets. Research on school choice suggests more options help families find schools that match their preferences, and competition between schools can increase school quality. Both these dynamics would theoretically reduce demand for private tutoring. Further, private tutoring markets overlap with mainstream schooling competition, insofar as private tutoring provides similar goods without offering a full substitute. Families can substitute a higher quality but more expensive mainstream schooling option with a cheaper mainstream schooling choice supplemented by private tutoring, or, given the similarity of goods, choose both the higher cost school and private tutoring.

Proportion private school enrollment is defined as the number of children enrolled in private school, out of the total such enrollees at either private or public school, according to the census and ACS. We choose proportion private enrollment as our measure of school choice, over charter enrollment or private school expenditures which were identified by the LASSO procedure, as upon further investigation the former demonstrated the most noticeable relationship after controlling for other covariates.

As shown in Figures 5 and 6, after controlling for other covariates, the model estimated coefficients for proportion private enrollment were small, all indistinguishable from zero, and though from the cross-sectional perspective there exists a positive trend in the observed, uncontrolled association, for the predicted-change perspective we see no such relationship. We again emphasize that proportion private school enrollment was the school choice predictor in our data set that was most saliently related to private tutoring prevalence.

Given that enrollment in private school generally requires greater investment than enrollment in public school, we might expect private-school families to be more secure and satisfied with their child's schooling. Survey data indicate that parents of students attending private schools express greater satisfaction with their child's school than do public school parents (Barrows et al., 2019). Why, then, if private tutoring demand supposedly increases with mainstream schooling dissatisfaction, would private tutoring be more popular in areas with greater private school enrollment? A simple explanation, akin to our interpretation for per capita income, is that families who desire maximal educational resources would enroll their children in both private school and private tutoring. The only barrier would be cost, though for families who can afford private school, private tutoring may not represent a significant burden. The fact that districts that had greater *declines* in private school enrollment saw greater *increases* in private tutoring corroborates this narrative of maximizing educational resources: if a student who would otherwise attend private school is now attending public school (e.g., unaffordable tuition, private school closure), the family may try to compensate by simultaneously enrolling in private tutoring. However, the question remains whether under causal circumstances families would view these options, mainstream schooling choice on the one hand and supplementary schooling on the other, as substitutes or complements.

Conclusion

In this study we combine data on the private tutoring industry and school-district characteristics to describe patterns in the private tutoring industry in the U.S. Private tutoring universally offers families additional resources for their children, though which families enroll in this service varies based on the specific features of a given education system. Beyond tutoring's effectiveness as an educational practice, basic questions about the industry, such as who enrolls in private tutoring, are consequential for understanding its impact. On one hand, providers through NCLB were enlisted to remediate students underserved by their mainstream school. On the other, Ochoa's (2013) qualitative study of a California public high school found that private tutoring was so widespread among high-achieving, high-income students that some of the school's teachers adapted the advanced classes' curricula to reflect the supplemental education that so many of their students received. This adaptation made the classes less accessible to high-achieving, low-income students.

Our study is to our knowledge the first to offer a comprehensive analysis of the growth and prevalence of private tutoring in United States. According to our data, private tutoring in the U.S. has grown precipitously in the last two decades, tripling the number of firms between 2000 and 2020. We selected variables for our multivariate analyses based on a LASSO procedure applied to two types of models: a cross-sectional model using only 2020 data, and a predicted-change model using changes in covariate and outcome values between 2000 and 2020. The LASSO results, and the subsequent non-parametric investigations, generally aligned with suggestions from relevant literature. Private tutoring exists disproportionately in the highest income and most educated areas, possibly driven by perceived competition among the highest performing students. Communities with a higher proportion Asian also had greater rates of private tutoring. The availability of private school options, though in some settings showing a negative relationship with demand for tutoring, had entirely insignificant associations with tutoring center prevalence after controlling for other covariates. We further observed that private tutoring is most closely associated with suburban districts, which suggests industry prevalence is not simply a function of population density, and districts that served high school students, which suggests private tutoring in the United States, as in many other countries with large tutoring industries, may be centered around college exam preparation.

Our study has several limitations. Our primary outcome variable, number of registered private tutoring firms per 1,000 children in a school district enrolled in public or private schools, imperfectly captures firms aimed specifically at K-12 education, assumes a tight relationship between number of firms and demand for private tutoring, and cannot detect individual-level patterns. The signal was, however, sufficiently strong to demonstrate clear relationships with our covariates at this aggregate level, and information on the supply side of private tutoring can be valuable in and of itself. Future investigations should endeavor to employ causal estimation strategies to uncover direct relationships between private tutoring and various facets of U.S. education, ideally with student-level data.

Private tutoring represents an increasingly relevant issue for education policy in the U.S. As a private industry it operates outside traditional regulations for educational institutions, but by offering a service that overlaps with mainstream schooling it may still affect students and learning outcomes. The appropriate policy response, if any, to a burgeoning private tutoring sector will depend on private tutoring's effects on American students and schools, a question ripe for further research.

Appendix A

Variable	Abbreviation	Data Source
Prop. population between age 5 and 19	Age0519	Census (2000); ACS (2020)
Prop. schools that are charter schools	ChrtrProp	CCD School level
Prop. population with at least a bachelor's degree	EduAtLstBch	Census (2000); ACS (2020)
Prop. population with at most a bachelor's degree	EduBch	Census (2000); ACS (2020)
Prop. population with a graduate degree	EduGrad	Census (2000); ACS (2020)
Prop. population with at most a high school degree or equivalent	EduHS	Census (2000); ACS (2020)
Prop. population with at most some college	EduSomeCol	Census (2000); ACS (2020)
Prop. students in public or private school enrolled in private school	EnrlPropPriv	Census (2000); ACS (2020)
Total district expenditures per student	Exp	CCD Fiscal
Elementary and secondary expenditures per student	ExpElSc	CCD Fiscal
Instructional expenditures per student	ExpInst	CCD Fiscal
Support service expenditures per student	ExpSprt	CCD Fiscal
District expenditures on charter schools	ExpCharter	CCD Fiscal
District expenditures on private schools	ExpPrivate	CCD Fiscal
Prop. families with a child under 18 present	FamChild	Census (2000); ACS (2020)
Prop. families that are married couples	FamMrrd	Census (2000); ACS (2020)
Prop. women age 15-50 that gave birth in last 12 months	FertBirthed	ACS (2009); ACS (2020)
Prop. women age 15-50 who gave birth in last 12 months that are married	FertBirthPropMrrd	ACS (2009); ACS (2020)
Between-school FRPL status dissimilarity index	FRLSegSch	CCD School level
Prop. population foreign born	ImmiForBorn	Census (2000); ACS (2020)
Income inequality GINI coefficient	IncGINI	ACS (2009); ACS (2020)
Median household income	IncMedHH	Census (2000); ACS (2020)
Income per capita	IncPerCap	Census (2000); ACS (2020)
Prop. schools that are magnet	MagnetProp	CCD School level
Prop. population lived abroad in the last 12 months	MbltyDffAbrd	ACS (2009); ACS (2020)
Prop. population lived in different county in the last 12 months	MbltyDffCounty	ACS (2009); ACS (2020)
Prop. population lived in different state in the last 12 months	MbltyDffState	ACS (2009); ACS (2020)
Prop. population lived in different town in the last 12 months	MbltyDffTown	ACS (2009); ACS (2020)
Prop. population lived in same house for the last 12 months	MbltySameHouse	ACS (2009); ACS (2020)
Median house value	MedianHouseVal	Census (2000); ACS (2020)
Prop. population in management, business, science, or art occupations	OccuMgmtBsnSciArt	Census (2000); ACS (2020)
Prop. population in production, transportation, moving occupations	OccuProdTransMvng	Census (2000); ACS (2020)

Prop. population occupied in resources, construction, maintenance	OccuRsrcCnstrMntn	Census (2000); ACS (2020)
Prop. population in sales or office occupations	OccuSalesOffice	Census (2000); ACS (2020)
Prop. population in service industry occupations	OccuService	Census (2000); ACS (2020)
Total students enrolled in Pre-K to 12th grade	PK12	CCD District Level
Prop. population with income over twice poverty level	PovOvrTwcPov	Census (2000); ACS (2020)
Prop. population with income under poverty level	PovUndr	Census (2000); ACS (2020)
Prop. population with income under half poverty level	PovUndrHlf	Census (2000); ACS (2020)
Total district revenue per student	Rev	CCD Fiscal
Revenue from federal sources per student	RevFed	CCD Fiscal
Revenue from local sources per student	RevLoc	CCD Fiscal
Proportion total revenue from local sources	RevPropLoc	CCD Fiscal
Proportion total revenue from state sources	RevPropSt	CCD Fiscal
Revenue from state sources per student	RevSt	CCD Fiscal
Ratio state source revenue to local source revenue	RevStToLoc	CCD Fiscal
Total Schools in District	Schls	CCD District Level
Schools per student	SchPerStd	CCD District level
Prop. students in designated special education	SpecEd	CCD District level
Ratio of students to administrators	StdAdmn	CCD District level Illinois and Utah data pulled from 2019-2020
Prop. students that identify as Asian	StdAsian	CCD School level
Prop. students that identify as Black	StdBlack	CCD School level
Prop. students designated free or reduced-price lunch	StdFRL	CCD District level Pulled from 2019-2020
Prop. students that identify as Hispanic or Latino	StdHisp	CCD School level
Ratio of students to teachers	StdTch	CCD District level Illinois and Utah data pulled from 2019-2020
Prop. students that identify as White	StdWhite	CCD School level
Total population	TotPop	Census (2000); ACS (2020)
Proportion total population that identify as American Indian	TotPropAmInd	Census (2000); ACS (2020)
Proportion total population that identify as Asian	TotPropAsian	Census (2000); ACS (2020)
Proportion total population that identify as Black	TotPropBlack	Census (2000); ACS (2020)
Proportion total population that identify as Hispanic	TotPropHisp	Census (2000); ACS (2020)
Proportion total population that identify as Native Hawaiian	TotPropNatHw	Census (2000); ACS (2020)
Proportion total population that identify as White	TotPropWhite	Census (2000); ACS (2020)
Urbanicity locale code	UrbnctyCode	CCD District level

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