Structuring College Access: The Market Segment Model and College Board Geomarkets

Ozan Jaquette (UCLA)   Karina Salazar (University of Arizona)

ABSTRACT

The Structure of College Choice (Zemsky & Oedel, 1983) created "Geomarkets" and the "Market Segment Model." Geomarkets carve states and metropolitan areas into smaller geographic units, meant to define local recruiting markets. The Market Segment Model predicts how student demand for a particular college varies by Geomarket, based on the socioeconomic characteristics of households. Geomarkets became an input for two College Board products that help colleges recruit students. First, the Enrollment Planning Service (EPS) software recommends specific Geomarkets and high schools from which colleges should recruit. Second, the Student Search Service sells the contact information of prospective students – referred to as "student lists" – and colleges can filter by Geomarket to determine which prospect profiles they purchase. We draw from scholarship on quantification, particularly the discussions of correlation and homophily by Chun (2021), to conceptualize how recruiting products incorporate Geomarkets. We address two research questions: What is the socioeconomic and racial variation between Geomarkets and how does this variation change over time? How does the socioeconomic and racial composition of included versus excluded prospects vary when student list purchases filter on particular Geomarkets? We answer RQ1 by analyzing Census data from 1980, 2000, and 2020. We answer RQ2 using data on student lists purchased by public universities, which we collected by issuing public records requests. We utilize a quantitative case study design. Metropolitan areas are cases. Analyses consist of descriptive statistics and interactive maps.

1 Introduction

On January 9, 2019 a public research university purchased College Board *Student Search Service* order no. 448922, thereby obtaining the contact information of out-of-state prospective students, who would subsequently receive brochures, postcards, email, and targeted social media. This was a large student list purchase, yielding $122,426$ "names." At \$0.45 per name, the order cost \$$55,091.70$. The order specified three "search filters" to control which names were purchased: first, the 2020 high school graduating class; second, under the heading "College Board Exams," PSAT score range of 1070 - 1180; and third, under the heading "Geography", the order filtered on 67 "Geomarkets," identified by titles like "IL08 - Northwest Suburbs" and "IL09 - North Shore."[1] The Geomarket filter carves states and metroplitan areas into smaller geographic units. Upon closer inspection, this student list purchase selected all Geomarkets in the Chicago-land area except for "IL10 - City of Chicago," which is significantly poorer and has a higher share of Black residents. Similarly, in the DC/Maryland/Virginia metro area, the order selected the affluent "MD02 - Montgomery Metropolitan," "MD03 - Central Maryland (w/o Baltimore)," "VA01 - Arlington & Alexandria," and "VA02 - Fairfax County" Geomarkets, but excluded the "MD05 - Prince Georges Metropolitan," "MD07 - Baltimore (Urban)," and "DC01 - District of Columbia" Geomarkets.

Sociology offers several perspectives to describe the process of sorting students into colleges as a process that tends toward social reproduction (Domina et al., 2017; Stevens et al., 2008). On the student demand side, the status attainment model argues that student postsecondary destination is a function of family socioeconomic background, particularly parental education (e.g., Blau & Duncan, 1967; Fishman, 2020; Karen, 2002; Sewell, 1971; Sewell & Shah, 1967). The cultural capital model argues that bourgeois households bestow the pedigree, social networks, and information necessary for their progeny to claim spots at selective colleges (Bourdieu, 1984, 1988; Huang, 2023) [ADD CITES]. Domina et al. (2017) describes schools as "sorting machines" that create, incorporate, and assign students to categories that determine educational opportunities, often reinforcing reinforcing racial and class inequality. On the supply-side, the credentialism literature recognizes that colleges have a financial incentive for educational credentials to be required to claim

[1] On the same day, the university purchased two additional orders that filtered on PSAT score ranges of $1190-1260$ and $1270-1520$, respectively, but selected the same HS graduating class and Geomarkets.

advantageous social and economic positions (Weber, 1948), and this race for credentials benefits affluent households (Labaree, 1997) [cite others]. Scholarship on enrollment management offers an agentic depiction of organizational behavior, showing that colleges expend considerable resources recruiting desirable prospects (Cottom, 2017; Holland, 2019; Salazar et al., 2021; Stevens, 2007).

We argue that these perspectives ignore an important mechansim of social reproduction: third-party vendors create products that sort students on behalf of college. These products often amplify historic inequality in educational opportunity by using past snapshots of student demand to make recommendations about where colleges should prioritize recruiting efforts. In the contemporary era of private equity funded platform capitalism, third-party recruiting products have become increasingly powerful, granular, and ubiquitous. However, we argue that a watershed moment in their development was the creation of Geomarkets.

In 1983, Robert Zemsky and Penny Odell authored *The Structure of College Choice*. College Board underwrote the project – providing data and funding – and published the book as part of their nascent efforts "to help colleges estimate their enrollment potential, efforts which had faltered largely because the smallest geographic unit used in these analyses was the state" (Zemsky & Oedel, 1983, p. x). Conceptualized as an effort to to "capture and quantify" (p. 11) the knowledge of admissions officers, Zemsky & Oedel (1983) developed the Market Segment Model by analyzing the SAT score-sending behavior of high school seniors in 1980. The thesis of the Market Segment Model is that student demand for your institution is a function of social class and geography. Therefore, colleges should recruit from territories that contain large populations of your target social class. Geomarkets are geographic borders meant to define local recruiting markets, a territory of an admissions recruiter. For instance, Figure X panel A shows Geomarkets in the Chicago-land area. As a planning tool for colleges, the Market Segment Model predicts how demand for a particular college varies by Geomarket, based on characteristics of households in the Geomarket.

Geomarkets have been incorporated into the supply-side structure of college access in three ways. Anecdotally, Geomarkets became an organizing principle for how college admissions offices allocate admissions recruiters to territories. Figure X panel B shows that Chicago Geomarkets define recruiting territories for University of Chicago admissions recruiters (Appendix Figures BLAH BLAH). Second, Geomarkets are the basis for the College Board Enrollment Planning Service (EPS). EPS software recommends which Geomarkets a college should recruit from and which schools/communities they should prioritize within targeted Geomarkets.

Third, Geomarkets were incorporated into College Board's student list product, Student Search Service. Student lists contain the contact information of prospective students and have been the primary source of lead generation in U.S. higher education since 1972, when College Board began selling names (Belkin, 2019; Jaquette et al., 2022). Ruffalo Noel-Levitz (2022b) reported that 87% of private and 86% of public four-year institutions purchase student lists. Colleges control which prospect profiles they purchase by selecting search filters, such as high school graduation year, SAT score, AP score, state, etc. Geomarket filters enable colleges to include or exclude prospects from particular Geomarkets.

Scholarship on enrollment management has focused on college behavior (e.g., Cottom, 2017; Salazar, 2022; Salazar et al., 2021; Stevens, 2007), contributing to the belief that recruiting is a function of individual colleges. However, scholarship has failed to investigate the broader enrollment management industry – consisting of third-party vendors, their products and consulting solutions – as a set of mechanisms that structure college access. These mechanisms, which lie upstream of the behavior of individual colleges, are incorporated by individual colleges in ways that funnel certain kinds of students to certain kinds of institutions. This omission is surprising given sociology is concerned with social sorting (Domina et al., 2017), particularly sorting into college.

This manuscript analyzes College Board Geomarkets as a case study of quantification. In particular, we draw from the discussions of correlation and homophily from Chun (2021). Zemsky & Oedel (1983) identified the correlates of 1980 SAT score-sending behavior and concluded that student demand for higher education is primarily a function of social class. The Market Segment Model argues that homophily – actors that share characteristics form connections – is the organizing principle of competition and college choice, stating that "the hierarchical structure of collegiate competition largely reflects the stratified social and economic dimensions of the communities from which colleges draw their students" (Zemsky & Oedel, 1983, p. 72). Scholarship on quantification demonstrates that making recommendations based on past correlations amplifies the effects of historic structural inequality (Burrell & Fourcade, 2021). The snapshot of student demand in 1980 – itself a consequence historic structural inequality – was programmed into recruiting products that colleges utilize to identify and target prospective students. The result is a supply-side that amplifies structural inequalities observed on the demand-side.

Our analyses address the two research questions, which speak to how Geomarkets are utilized within EPS and within the Student Search Service student list product. First, what is the socioeconomic and racial variation between Geomarkets in metropolitan areas and how does this variation change over time? We address this question by spatially joining Geomarket shapefiles to Census data about socioeconomic and racial characteristics. Second, how does the socioeconomic and racial composition of included versus included prospects vary when student list purchases filter on particular Geomarkets? This research question is motivated by Zemsky & Oedel (1983), which recommends that selective colleges target affluent Geomarkets. Additionally, prior research on enrollment management behavior finds that selective colleges focus recruiting visits on high schools in affluent, predominantly white communities (Salazar et al., 2021; Stevens, 2007). We analyze this research question using data from actual student list purchases, which were collected using public records requests. We analyze student list purchases that include all Geomarkets in a metropolitan area in order to simulate which prospects would be included or excluded had the student list purchase filtered on particular Geomarkets.

The following section introduces background and scholarship about enrollment management and introduces salient concepts from scholarship on quantification. Second, we introduce the case, describing how Zemsky & Oedel (1983) developed Geomarkets and the Market Segment Model and how these concepts were incorporated into College Board recruiting products. Third, we describe data and methods. Fourth, we present results. [We find that…?PARAGRAPH ON RESULTS?]

Finally, we discuss implications for scholarship and for policy. The sociology of education should move beyond the fixation on schools and policies as the primary sorting machines. DiMaggio & Powell (1983) [p. 148] remind us that the organizational field includes the totality of relevant actors." Third-party vendors have structured college access for decades and their influence is growing. The contemporary enrollment management industry is characterized by private equity owned firms selling software-as-service platforms that utilize the same logic as Zemsky & Oedel (1983), for example EAB's "pipeline analytics" machine learning product [CITE]. By investigating high-leverage actors and products in the organizational field, sociology can develop important insights that shape future federal and state regulatory policy. [REVISE THIS PARAGRAPH]

2 Enrollment Management and Quantification

Enrollment Management

Enrollment management is simultaneously a profession, an administrative structure, and an industry. As a profession, enrollment management (EM) integrates techniques from marketing and economics in order to "influence the characteristics and the size of enrolled student bodies" (Hossler & Bean, 1990, p. xiv). As an administrative structure, the EM office typically controls the activities of admissions, financial aid, and recruiting (Kraatz et al., 2010).

Figure 1 depicts the "enrollment funnel," which modifies the traditional "marketing funnel" to depict broad stages in the process of recruiting students (EAB, 2019; Litten et al., 1983). The funnel begins with a large pool of "prospects" (i.e., prospective students) that the university would like to enroll. "Leads" are prospects whose contact information has been obtained. "Inquiries" are prospects that contact the institution, including those that respond to an initial solicitation (e.g., email) and those that reach out on their own (e.g., sending SAT scores). The purpose of the enrollment funnel is to inform recruiting interventions that target one or more stages. These interventions seek to increase the probability of "conversion" across stages (Campbell, 2017). At the top of the enrollment funnel, purchasing student lists is the primary means of converting prospects to leads (Jaquette et al., 2022). Purchased leads are served emails, brochures, and targeted social media designed to solicit inquiries and applications (Ruffalo Noel-Levitz, 2022b).

Scholarship at the nexus of enrollment management and college access can be categorized by which part(s) of the enrollment funnel it speaks to. The majority of scholarship focuses on the admissions stage, analyzing which admissions criteria are utilized and/or which applicants are admitted (e.g., Hirschman et al., 2016; Killgore, 2009; O. Y. A. Poon & Bastedo, 2022; Posselt, 2016; Taylor et al., 2024). Scholarship from the economics of education often investigate financial aid leveraging, which seeks to convert admits to enrolled students (Hurwitz, 2012; e.g., Leeds & DesJardins, 2015).

A growing literature analyzes the earlier "recruiting" stages of identifying leads, soliciting inquiries, and soliciting applications. Salazar et al. (2021) conceptualize recruiting behavior as an indicator of college enrollment priorities. Ethnographies by Stevens (2007) and Khan (2011) identify connections between private school guidance counselors and college admissions officers as a mechanism for social reproduction. In turn, recruiting visits to high schools – and subsequent phone calls – are a means of maintaining ties with guidance counselors at feeder schools and establishing relationships with prospective students (Ruffalo Noel-Levitz, 2022b; Stevens, 2007). Quantitative case-studies of off-campus recruiting visits by public research universities and by selective private universities reveal a preference for visiting private schools and affluent, predominantly white public schools (Jaquette et al., 2024; Salazar, 2022; Salazar et al., 2021). From the student perspective, Holland (2019) finds that underrepresented students were drawn to colleges that made them feel wanted, often attending institutions with lower graduation rates and requiring larger loans than other college options. Cottom (2017) shows that for-profit colleges found a niche in Black and Latinx communities because traditional colleges ignored these communities.

By focusing on the behavior of colleges, scholarship on EM implicitly states that recruiting is something done by individual colleges. The broader EM industry includes relevant stakeholders in the organizational field (DiMaggio & Powell, 1983), including professional associations (e.g., National Association for College Admission Counseling) and third-party servicers (e.g., College Board, EAB) that supply products and consulting solutions to colleges. We argue college access is structured by third-party servicers and products that interact with direct-providers (colleges). Although sociologists have hinted at the ways enrollment management contributes to inequality in college access (e.g., Kraatz et al., 2010), scholarship has failed to make third-party servicers and products the object of empirical analysis.

Drawing from scholarship on organizational theory, enrollment management processes require colleges to make many “make or buy” (Coase, 1937; Scott & Davis, 2007) decisions about whether to perform a given task in-house or outsource it to a third-party vendor (Jaquette et al., 2022). Unfortunately, few empirical studies make EM vendors or products the object of empirical analysis. The most widely-known class of EM vendor is EM consulting firms, which provide advice and implementation in the areas of marketing, recruiting, pricing and financial aid, and student success. As “creating a class” has becomes complicated and high-stakes (Stevens, 2007), many colleges hire EM consulting firms to develop and/or implement recruiting campaigns. The two largest firms –

Ruffalo Noel Levitz and EAB – claim to serve more than 3,000 colleges and universities collectively (EAB, n.d.; Ruffalo Noel Levitz, 2023).[2]

While the contemporary EM industry is characterized by software-as-service products sold to colleges by private equity backed firms (Jaquette et al., 2022), College Board products played a pivotal role in transforming recruiting from an in-house process to a process structured by third-party products. Every year, colleges must figure out which prospects should receive promotional material and which high schools to visit. The Student Search Service – created in 1972 and copied by ACT's Educational Opportunity Service – became the ubiquitous means of converting prospects into leads that could be served targeted recruiting interventions. The Enrollment Planning Service (EPS), launched in 1984, is an early software-as-service product that provides recommendations about which Geomarkets colleges should recruit from and which high schools they should visit within targeted Geomarkets. Both products are applications of quantification. Student Search Service includes or excludes prospects from a student list purchase based on value of selected filters like Geomarket while EPS encourages colleges to target Geomarkets and high schools based on the characteristics of households. The multi-disciplinary literature on quantification helps conceptualize how third-party products utilize Geomarkets and the potential consequences of this utilization on equality of opportunity.

Quantification

Espeland & Stephens (2008, p. 402) define quantification as "the production and communication of numbers" (p. 402). Reacivity, discipline, and authority are three interrelated themes that describe the effects of quantification. *Reactivity* is the idea that salient quantitative measures cause people and organizations to change their behavior. Quantification *disciplines* actors to react in particular ways. Quantification changes decision-making power *authority*, often weakening the discretion of local decision-makers. For instance, scholarship about U.S. News & World Report (USNWR) law school rankings demonstrate the effects of quantification (Espeland & Sauder, 2007, 2016; Sauder, 2008; Sauder & Espeland, 2009). Law school rankings were developed as a means of informing prospective students about the relative quality of different programs. Rankings affect (reactivity)

[2]In our data collection, attempting to obtain data about student list purchases from all public universities in four states, at least half of these universities outsourced student list purchases to an EM consultancy (Jaquette et al., 2022; Salazar et al., 2022).

where students apply and enroll (Espeland & Sauder, 2016). Rankings also affected hiring decisions of firms because clients evaluated firms based on the prestige of law schools attended by firm lawyers. Once law schools realized that "important groups of constituents — students, faculty, trustees, employers, other media — were using rankings to make decisions that had large consequences for schools …[then] schools felt pressured to take them seriously" (Espeland & Stephens, 2008, p. 415). Rankings *disciplined* the behavior of law schools. For example, characteristics valued by the rankings system (e.g., LSAT scores) became more important for decisions about admissions and merit aid (Espeland & Sauder, 2016). Rankings also weakened the *authority* of admissions personnel to make independent decisions about class size and which applicants to admit (Espeland & Sauder, 2016).

The analysis of UK school "league tables" by McArthur & Reeves (2022) shows how quantification can be a mechanism of social reproduction. In 1992, the UK government began publishing school league tables, which ranked schools based on student performance on national exams taken at age 16. League tables facilitate making evaluative comparisons between schools regardless of geographic proximity. They also discipline households and schools to conceive of school quality in terms of test scores, which are substantially a function of the class composition of schools. Using Census data measured at the local authority level (similar to a U.S. county), McArthur & Reeves (2022) find that localities with higher performing schools experienced growth in the share of managerial/professional households following the adoption of league tables and a decline in the share of working-class households. Using longitudinal survey data, managerial/professional households were more likely to move to localities with higher ranked schools following the introduction of school league tables. The introduction of league tables contributed to social reproduction because professional/managerial households were more aware of these consumer-facing metrics and had resources to respond by moving to more expensive neighbhorhoods, near higher performing schools.

Correlation. The interdisciplinary literature on quantification (Mennicken & Espeland, 2019) includes important contributions from the field of critical data studies (e.g., Noble, 2018; O'Neil, 2016). In particular, the discussions of correlation (chapter 1) and homophily (chapter 2) by Chun (2021) introduce ideas salient to the analysis the Market Segment Model and Geomarkets. Correlation measures the extent to which two or more variables move together. Predictive analytics are based on correlation and are developed in two steps. First, apply statistical techniques to previous cases (training data) in order to identify factors positively and negatively associated with an outcome of interest. Second, apply these results (e.g., regression coefficients) to future cases in order to make predictions and/or to assign levels of risk to each case. Chun (2021) provides the example of Kosinski et al. (2013), who develop a method to predict sensitive personal attributes (e.g., gender, political party) based on Facebook Likes. These models predict outcomes based on correlations without requiring knowledge about underlying causal relationships. Chun (2021, p. 50) writes that

> correlation grounds big data's so-called revolutionary potential. As Wired editor Chris Anderson infamously declared ..., big data proved that 'correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all.'

Due to data limitations, predictive analytics often utilize "proxy" variables (Chun, 2021; O'Neil, 2016), which are variables that are correlated with a variable of interest. For example, "e-scores" utilize proxy variables to identify "people like you" and then predict your buying behavior based on the past buying behavior of people like you. O'Neil (2016, p. 146) states that "the modelers for e-scores have to make do with trying to answer the question 'How have people like you behaved in the past?' when ideally they would ask, 'How have you behaved in the past?' " We observe similar behavior in market research about college access, when enrollment managers use 'which colleges did students near you consider' as a proxy for, 'which colleges would you consider?'

Many studies show that predictions based on correlations reproduce structural inequality (for a review see Burrell & Fourcade, 2021). The correlations observed during the training data stage are a snapshot of relationships between variables at a particular point in time. Observed correlations may be a function of enduring structural inequality, but underlying causes are not considered by applications of predictive models. Reviewing scholarship about algorithms, Burrell & Fourcade (2021, p. 224) state that "predicting the future on the basis of the past threatens to reify and reproduce existing inequalities." Disproportionately targeted/excluded populations are predicted to have a higher risk of an outcome, which amplifies subsequent targeting/exclusion. This phenomenon has been termed the "ratchet effect" (Harcourt, 2015) and "pernicious feedback loops" (O'Neil, 2016).[3] As we discuss below, Zemsky & Oedel (1983) analyzed 1980 score-sending behavior (training data) and inferred that demand for college is a function of class. They then recommended that selective colleges recruit from localities that have a high share of affluent, college-educated households.

Homophily. Homophily is the idea actors who share common characteristics are likely to form connections with one another, or "birds of a feather flock together" (McPherson et al., 2001). Homophily is a core concept of network science, in which actors (nodes) are connected to one another directly and indirectly via network ties (edges). In *The company We Keep: Colleges and Their Competition*, Zemsky & Oedel (1983, Chapter 4) conduct a network analysis whereby two colleges are defined as competitors if a large number of students submit SAT scores to both colleges. Chun (2021) argues that because network science models often draw from rational choice theory, they assume that homophily is the result of voluntary action by individuals.

Chun (2021) problematizes the idea that homophily is a naturally occurring phenomenon. Because network science models – like correlational models above – typically do not observe how historical structures affect relationships, they "erase historical contingencies, institutional discrimination, and economic realities" (Chun, 2021, p. 95) that cause behavior consistent with homophily. Second, in commercial social networks, homopphily is more than an assumption; rather, it is programmed into algorithms that create connections between users. Thus, "social networks create and spawn the reality they imagine; they become self-fulfilling prophecies" (Chun, 2021, p. YY). We observe similar phenomena in our case. Based on a snapshot of 1980 SAT score-sending, Zemsky & Oedel (1983) concludes that like-colleges compete for like-students (i.e., students of similar social origin). In turn, Zemsky & Oedel (1983) reasons that colleges should target the Geomarkets and high schools targeted by peer colleges. This logic is subsequently programmed into EPS software that recommends which Geomarkets and high schools to recruit from. Thus, homophily observed on the demand side – which is a function of historic structural inequality — is programmed into the supply-side.

[3] An often cited example is the LSI-R recidivism model which predicts a prisoner's chances of re-arrest and is used by 24 states (O'Neil, 2016). Because the algorithm uses zip code as an input, people who live in highly policed neighborhoods have a higher predicted probability of being arrested, which leads to more policing in those neighborhoods, which perpetuates racialized inequality in arrests. Note that predictive models such as the LSI-R model are not merely used for social science purposes. Rather, they reproduce structural inequality because they direct the allocation of future resources based on a snapshot of historical inequality.

Homophily is central to market research products that categorize customers. Geodemography emerged in the 1970s as a branch of market research that estimates the behavior of consumers based on where they live (Burrows & Gane, 2006). Market segments are subgroups within a larger market that have similar consumer demand. Early geodemographic classifications of consumers (e.g., PRIZM by Claritas Corporation) were derived from publicly available Census data, which disaggregated data to the zip code level. The Claritas Corporation had a financial incentive to argue that people living near one another share similar consumer preferences because geographic localities could then be categorized into market segments that would be useful for direct mail marketing campaigns (McKelvey, 2022). Later, the development of individual credit scores (e.g., FICO score) enabled merchants to classify consumers into many, fine-grained groups (M. Poon, 2007). Fourcade & Healy (2013) introduce the concept "classification situations" to describe the expansion of actuarial techniques to categorize customers into many, ordinally ranked groups. Merchants and lenders began tying these classifications to tiered products that targets different consumer groups with different levels of benefits and costs (Fourcade & Healy, 2024).[4] Classification situations engender markets where a vertical hierarchy of products are matched to a vertical hierarchy of consumers. We observe similar processes in our case study. Zemsky & Oedel (1983) categorizes students into four market segments – local, in-state, regional, and national – based on their score sending behavior and then evaluates the attractiveness of each Geomarket based on how many "regional" and "national" students live there.

We make targeted contributions to scholarship on quantification in the sociology of education. First, in the case of college rankings, extant research shows how consumer-facing quantification disciplines the application/enrollment behavior of prospective students, the hiring behavior of employers, and the behavior of colleges that are disciplined to pursue customers with characteristics valued by rankings (Espeland & Sauder, 2007, 2016; Sauder & Espeland, 2009). As Stevens (2007) demonstrates in the chapter *Numbers*, EM is fundamentally concerned with quantification. However, sociological analyses of enrollment management focus on the behavior of colleges and their agents, yielding the implicit belief that inequalities created by EM are a function of individual colleges reacting to rankings and other macro structures in their environment. To our knowledge, the sociology of edu-

[4] For example, "payday loans" charge high interest rates to consumer groups that were previously denied credit altogether.

cation has not considered producer-facing products that quantify students on behalf of producers. Market research and investigative journalism indicates that the vast majority of colleges purchase third-party EM products to identify prospects and to decide which schools and communities to target [Marcus (2024);]. Drawing from scholarship from critical data studies (e.g., Benjamin, 2019; Chun, 2021; O'Neil, 2016), recruiting products grounded in the logic of predictive analytics take a snapshot of student demand – without considering historical structures that produce inequality – and then recommend that colleges divert recruiting resources to localities with strong student demand. Based on a snapshot of existing social stratification, market research matches verticially categorized consumers to vertically categorized producers, thereby amplifying the effect of initial stratification on subsequent stratification. Third-party EM products have been sold since the 1980s and have become more abundant with the ubiquity of software-as-service platforms, but have remained invisible to sociologists. We make third-party EM products the object of empirical analysis, though we cannot claim to assess how the population of colleges utilize these products.

This manuscript analyzes Market Segment Model (Zemsky & Oedel, 1983), which categorized high school students into vertical market segments – local, in-state, regional, national – and simultaneously created local Geomarkets that could be evaluated based on their composition of student market segments. The Market Segment Model and Geomarkets became the basis for the College Board *Enrollment Planning Service* (EPS), which advised colleges which Geomarkets to target. Later, Geomarkets were incorporated into the College Board student list product named Student Search Service. Unlike the analysis of UK school league tables, McArthur & Reeves (2022) we cannot show the effect of quantification on social reproduction. However, by showing which students are included/excluded in student list purchases that filter on particular Geomarkets, our analyses provide novel insight into the underlying mechanism by which quantification can reproduce historical class-based and race-based inequality in educational opportunity.

3 The Market Segment Model and College Board Geomarkets

Creating Geomarkets and the Market Segment Model.

In 1978, set against the backdrop of impending college-age demographic decline, University of

Pennsylvania professor Robert Zemsky, was tasked by the President to figure out, " 'Who thinks about Penn?' " and "'What other institutions do they think about when they think about us?" (Zemsky & Oedel, 1983, p. x). To answer these questions, Zemsky began working with the Market Research Committee of the Consortium on Financing Higher Education (COFHE), a consortium of 30 selective private universities founded in the mid-1970s. The project goal became the creation of the Market Segment Model, which had the lofty ambition of predicting student demand for any college from any locality. However, "to gain a truly comprehensive view of the collegiate enrollment market, we needed a database that described most institutions and most students" (Zemsky & Oedel, 1983, p. x). The group approached College Board. "Coincidentally, the Board was reviewing its own efforts to help colleges estimate their enrollment potential, efforts which had faltered largely because the smallest deomgraphic unit used in these analyses was the state" (Zemsky & Oedel, 1983, p. x).

Although the analyses of Zemsky & Oedel (1983) are based on the score-sending behavior of SAT test-takers, the authors had great respect for admissions officers and conceived of the project as an effort to "capture and quantify" (p. 11) their knowledge:

> Admissions officers invariably are tellers of stories – about the colleges they represent, about the colleges they attended, about each other, and about the often vagabond life of college recruiting (p.9)...We have begun with this celebration of sotrytelling...[because] we believe that the intuitios of admissions officers actually comprise a remarkably systematic body of knowledge about the college selection process...Our research this is based opn listening carefully to what admissions officers have to say (pp. 9-10).

The "initial task" was to define geographic boundaries "in a manner consistent with admissions officers' intuitive understanding of student pools" (Zemsky & Oedel, 1983, p. 4). Quoting an admissions officer, Zemsky & Oedel (1983) [p. 11] write, " 'There are only three kinds of college-bound students: those who want to live at home, those who want to live on campus but bring their laundry home, and those who want to go far enough from home that Mom and Dad can't visit without calling first.' " As such, Zemsky & Oedel (1983, p. 11) created "three types of boundaries – region, state, and community. The initial regions in the project were New England, Middle States, and the South. Next, they"divided each state into as few as two and as many as thirty community-based enrollment markets or pools, for a total of 143 separate markets" (p. 11). These enrollment markets, later called Geomarkets, were intended to be consistent with the conception of a catchment market from the perspective of admissions counselors. Zemsky & Oedel (1983, pp. 11–12) described the creation of Geomarket borders only briefly:

> In many cases, the market boundaries match formal political and educational divisions, reflecting natural channels of communication. Each major metropolitan area is composed of several markets, usually corresponding to the inner city, a first ring of suburbs, and an outer ring of suburbs. In more sparsely populated areas, communities are sometimes combined in order to make the analysis meaningful."

Having defined geography, the Market Segment Model sought to predict how student demand for a particular college varies by Geomarket, based on the characteristics of households in the Geomarket:

> For our analysis, we sought not a complex mathematical model, but a straightforward classification system that would track the pattern of SAT-score submissions to create a map of student choice. The Market Segment model that we developed was nothing more than a set of simple rules for disaggregating high school seniors into similar groups. The model worked because students, once so disaggregated, appeared to behave in remarkably consistent ways (Zemsky & Oedel, 1983, p. 4).

SAT test-takers were categorized into one of four different *market segments* – local, in-state, regional, and national – based on SAT score-sending behavior. For a given student, each college that receives a score from the student can be defined as "local" (college located in the the same Geomarket as the student), "in-state" (same state but different Geomarket), "regional" (same region but different state), or "national" (different region). In turn, a test-taker is categorized in the "local" market segment if they submit more SAT scores to local institutions than they do to in-state, regional, or national institutions. An "in-state" student submits more SAT scores to in-state institutions than they do to local, regional, or national institutions, etc.

The two primary outputs of the Market Segment Model are the (1) Market Segment Profile and (2) the Institutional Profile. Appendix A describes these outputs in more detail. Both outputs are created separately for each Geomarket. For each market segment (local, in-state, regional, national), the Market Segment Profile shows the number of students, their average SAT score, the percent aspiring to a BA+, percent with family in come greater than $35,000, percent with both parents having a BA, etc.[5] The Institutional Profile shows the number of students who send scores to a particular institution – separately by market segment – and which majors these students are interested in. A university could obtain this for their own institution or for a competitor.[6] Taken together, the Market Segment Profile shows a colleges which Geomarkets possess attractrive student market segments while the Institutional Profile shows the extent to which students in a particular Geomarket are interested in your college or a competitor college. These outputs became the basis for the Enrollment Planning Service (EPS) software.

Correlations. Zemsky & Oedel (1983, Chapter 3), *A Sense of Place: Students, Families, and Communities*, identifies the student characteristics correlated with being in the local, in-state, regional, or national market segment. The analyses identify four variables – educational aspirations, parental education, scholastic aptitude, and family income – that predict score sending behavior, both individually and in combination. Because these four variables "reflect the basic social patterns of the nation, it would have been surprising if these were not the four social variables that best explained the patterns of college choice" (Zemsky & Oedel, 1983, p. 33).

The thesis of Chapter 3 is that student demand for higher education is a function of social origin. For the authors (p. 33) state that "these data allow us to say with considerable confidence that local and in-state students are not likely to come from families in which both parents have received college educations" and that "the implication is simply that college-educated parents instill in their children more wide-ranging educational aspirations." Commenting on family income, Zemsky & Oedel (1983) [p. 33] write that "we could predict that all local students would come from moderate-income or low-income families and be wrong only 5.5 percent of the time."[^7] Zemsky & Oedel (1983, p. 42) conclude that "our research has simply demonstrated what everyone has always known: communities with high levels of family income and parental education are also communities in which students have higher than average SATs and more far-reaching aspirations." The authors

[5] For example, Appendix **?@tbl-market-segment-characteristics** shows how many students in "CT3 – Fairfield County" are defined as regional or national based on their SAT score-sending behavior.

[6] Appendix **?@tbl-sample-institutional-profile** reproduces a partial, simplified version of Zemsky & Oedel (1983, fig. 2.3), the Institutional Profile of an anonymous college for students from Fairfield County, CT. This table shows that 69 Regional students and 109 National students from Fairfield County sent SAT scores to the college.

also find that these four variables predict student score-sending behavior at the Geomarket-level. However, Geomarkets differ in the relative abundance of students with particular socioeconomic characteristics, which has practical implications for recruiting. Therefore, Zemsky & Oedel (1983, p. 44) recommend that colleges target Geomarkets with desirable compositions of socioeconomic characteristics in order to reach students from desired student market segments:

> On occasion, senior spokespersons for the profession worry that students outside the main [Geo]market areas remain forgotten and hence, unchallenged. Inevitably, the increasing competition for students, the expense of travel and mailings, and internal political constraints compel institutions to concentrate their efforts where they will do the most good. The result is a natural reinforcing of the basic socioeconomic patterns that gave shape in the first place to the structure of college choice.

Homophily. *The Company We Keep: Colleges and Their Competition* (Zemsky & Oedel, 1983, Chapter 4) conducts a network analysis to determine which institutions are in competition with one anothyer.[7] Based on these analyses, Zemsky & Oedel (1983) [p. 46] state that competition between colleges is characterized by homophily: "we draw a fundamental conclusion about the structure of college choice: collegiate competition occurs principally between like institutions." Subsequent analyses investigate the tuition price and the socioeconomic composition of institutions in competition with one another. Private selective colleges and private flagship universities compete directly for students, charge the highest prices, and enroll students with the highest socioeconomic status. The authors argue that like-colleges compete for like-students as defined by socioeconomic characteristics. Zemsky & Oedel (1983, p. 72) describe observed patterns as a natural process in which a vertical socioeconomic hierarchy of students is matched to a vertical hierarchy of universities:

> Students describe themselves socially simply by telling us the colleges and universities

[7]This is a "two-mode" social network in which students (mode 1) send SAT scores – the network tie – to colleges (mode 2). The authors turn this into a one-mode college network that defines two institutions as being in competition with one another – the network tie – if at least 15% of students who sent SAT scores to one institution also sent scores to the other institution and vice-versa. Next, the authors develop "tinker toy" diagrams that show which institutions are connected to one another. These diagrams are drawn separately for each student segment – local, in-state, regional, and national – and separately for each geomarket, such that the analyses convey which institutions compete with one another for which student segments in each local market. For example, describing the Figure 4.4 "Structure of Fairfield County Regional Market," (Zemsky & Oedel, 1983, p. 54) state that "competitive overlap, moreover, is often confined to institutions belonging to the same [Carnegie] type as well sector. For example, public flagships compete primarily with other public flagships; private standard colleges, with other private standard colleges; Catholic institutions, with other Catholic institutions."

> in which they are interested. The layering of collegiate competition is primarily a socioeconomic layering. The hierarchical structure of collegiate competition largely reflects the stratified social and economic dimensions of the communities from which colleges draw their students. Competition among colleges, as admissions officers have told us for so long, is in fact, a matter of keeping company with one's peers.

The discussion of competition by Zemsky & Oedel (1983) exemplifies the concerns about correlation and homophily described by Chun (2021). A correlational analysis of 1980 SAT score-sending patterns finds competition between colleges is defined by socioeconomic homophily. This homophily is presented as a naturally occurring phenomenon. Given these findings, Zemsky & Oedel (1983) recommend that colleges should target Geomarkets that contain a critical mass of students interested in peer-coleges, information that can be discerned from the Institutional Profiles (Appendix **?@tbl-sample-institutional-profile**). In itself, Zemsky & Oedel (1983)'s Market Segment Model is a social science depiction of student demand – akin to the status attainment model – that does not consider historic, structural inequalities that cause observed patterns. However, by inscribing the Market Segment Model and Geomarkets into the EPS software, College Board amplified structural inequalities that contributed to homophily observed in 1980 SAT score-sending beahivor. In this way, commodification of the Market Segment Model and Geomarkets "engineers homophily" (Chun, 2021).

Enrollment Planning Service. In 1984, College Board created the Enrollment Planning Service (EPS), based on the Market Segment Model (College Board, 2012; Takamiya, 2005). EPS was an early software-as-service platform that recreated the analyses of Zemsky & Oedel (1983). For each Geomarket, colleges could obtain Market Segment Report for each local market and the Institutional Profile – their own and that of competitors. Based on background conversations with enrollment management professionals, EPS software also provided information about the score-sending behavior of individual high schools within each Geomarket. Therefore, colleges used EPS software to decide which Geomarkets to recruit from and which high schools to visit within targeted Geomarkets. Typical College Board (2005) marketing material describes EPS as,

> The marketing software that pinpoints the schools and Geomarkets where your best prospects are most likely to be found. With the click of a mouse, EPS provides you

with comprehensive reports on your markets, your position in those markets, and your competition. Focus your valuable time and resources on the right prospects.

Whereas Zemsky & Oedel (1983) identified 143 Geomarkets covering the New England, Middle States, and South region, EPS created Geomarkets for the remaining U.S. states, with 304 Geomarkets in total. College Board (2023) shows the contemporary Geomarkets. Documentation and promotional material suggests that geomarket borders were chosen based on a combination of formal geographic borders (e.g., counties) as well as proprietary College Board data designed to identify geographic areas with different college-going behaviors.[8] However, Geomarkets for New England, Middle States, and the South are identical to those developed by Zemsky & Oedel (1983).

E. P. Berman & Hirschman (2018) argue that quantification has effects to the extent that stakeholders care about the numbers. Market research suggests that EPS was highly salient. Noel-Levitz (1998) reports that in 1995, 37% of 4-year publics and 49% of 4-year privates used EPS, while 41% of 4-year publics and 16% of 4-year privates used ACT's market analysis service product.

EPS software may "discipline" (Espeland & Stephens, 2008) colleges to approach recruiting in a manner consistent with the Market Segment Model. Drawing from promotional literature (e.g., College Board, 2005, 2011a), Takamiya (2005), and background conversations with enrollment managers, the practical purpose of EPS was to inform the "travel schedule" of admissions recruiters. EPS promotional material and user guides encourages users to begin by identifying which Geomarkets they will recruit from.[9] Second, EPS users decide which high schools they will visit within selected Geomarkets. Based on the principle of homophily, the Market Segment Model suggests that selective colleges should target Geomarkets with large numbers of affluent, college educated households, while low-income communities are left to local four-year and community colleges.

EPS may also weaken the authority of local decision-makers. Zemsky & Oedel (1983) sought to develop a concrete, data-driven framework – The Market Segment Model – that replicates

[8] College Board (n.d.) states that "geomarkets are areas within a state that represent a further segmentation of a population. Students from California don't all share the same college-going behaviors. We have accounted for this variance by segmenting the 50 states into 304 geomarkets to provide further insight into student behaviors within particular areas of individual states."

[9] Software documentation by Oracle (n.d.) states that, "EPS market codes are proprietary market codes owned by the College Board and are used to categorize external organizations and people into geographical areas.... Some admissions offices use EPS market codes to focus their recruiting efforts in geographic areas in which they believe they will be the most successful."

the aggregate knowledge of local admissions officers. Once this knowledge was quantified and commodified onto a CD-ROM, the local expertise of admissions officers becomes less valuable. The EPS product increases the ability of a college admissions leader – working with College Board staff or an enrollment management consultant – to plan recruiting efforts centrally. In background conversations, enrollment management professionals told us that EPS software enabled colleges to plan travel without relying on admissions officers having strong local knowledge of their territories. However, EPS software often recommended visiting the same sets of affluent, high-achieving high schools that were receiving visits from other colleges. We were told that savvier, quantitatively-adept admissions offices used EPS to visit schools that EPS recommended ignoring because there would be less competition for the good students who attended these high schools.

Finally, we suspect that Geomarkets affect how admissions offices organize the recruiting territories assigned to each admissions officer. Geomarkets were created to mirror the territories of admissions officers (Zemsky & Oedel, 1983). In turn, as Geomarkets became more salient, admissions offices often structured their territories around Geomarkets. On background, admissions officers and enrollment consultants told us it remains common parlance to hear an admissions officer say something like, "I recruit 'PA 2'," which refers to the "Chester County, PA Geomarket. In states a college recruits heavily from, admissions officers are often assigned specific Geomarkets as their territory. This can be seen in the Chicago-land recruiting territories of University of Chicago [ADD TO APPENDIX], of Lake Forest College, of Saint Mary's College [ADD TO APPENDIX CRYSTAL]

Although we cannot gain access to EPS software, Geomarkets are fundamental to EPS software and (arguably) to the organization of recruiting territories for many colleges. Therefore, we are interested in the extent to which this building block is associated with race and class. Research question 1 asks, what is the socioeconomic and racial variation between Geomarkets and how does this variation change over time? We focus on metropolitan areas that are associated with three or more Geomarkets.

We expect substantial socioeconomic inequality between geomarkets in large metropolitan areas. Given the extent of class- and race-based residential segregation in the U.S., it would be surprising to not observe such inequality. Moreover, Zemsky & Oedel (1983) viewed demand for higher education as a function of class and developed Geomarkets with an eye towards identifying geographic areas that differed from one another in terms of class composition.

We also expect substantial racial inequality between geomarkets in large metropolitan areas. Interestingly, the Market Segment Model is explicitly based on socioeconomic stratification, but Zemsky & Oedel (1983) do not mention race. U.S. cities are characterized be extreme historic and contemporary residential racial segregation (Korver-Glenn, 2022). Structures built upon racialized structures are racialized structures (Norris, 2021). Unless designers intentionally consider racial segregation, selection devices that categorize people based on geographic location are likely to reproduce historical race-based inequality in opportunity (Chun, 2021). Second, although geomarket borders may have been drawn along class divides, a strong correlation exists between race and wealth (Kraus et al., 2019). Third, Geomarket borders may have been drawn in a way that follows the countours of racial segregation in residential housing. Examples include: the "South and South Central Los Angeles" geomarket (CA21); the "City of Oakland" geomarket (CA07), which is surrounded by the "Alameda County excluding Oakland" geomarket (CA08); and the "Wayne County Detroit" geomarket (MI01), which is surrounded by the "Detroit's Northern Suburbs" (MI02) and "Ann Arbor" (MI03) geomarkets.

Geomarket Filter in Student Search Service. A student list contains the contact information of prospective students who meet the search filter criteria (e.g., test score, GPA) specified by the university. Student lists are the fundamental input for undergraduate recruiting campaigns because purchased names – alongside prospects who reach out on their own – constitute the set of prospects who receive subsequent recruiting interventions (e.g., mail, email) designed to push them toward the application and enrollment stages of the "enrollment funnel." Ruffalo Noel-Levitz (2022b) reports that 86% of public colleges and 87% of private colleges purchase student lists.[10] Historically, dominant list vendors are college board and ACT, which derived student list data from test-takers, but the test-optional movement, advances in technology, and surging private equity investments have contributed to new sources of student list data (Jaquette et al., 2022).

[10]For public universities that purchased lists, 80% purchase more than 50,000 names annually. Ruffalo Noel-Levitz (2022a) reports that student lists were the top expenditure item in the undergraduate recruiting budget for both private and public institutions in 2022, with the average public institution allocating 15% of its budget to purchasing names.

Student lists are positively associated with student outcomes. A College Board research report by Howell et al. (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing colleges to purchase their contact information – to those who opted out. After controlling for covariates (e.g., SAT score, parental education, school fixed effects), 41.1% of students who participated in Search attended a 4-year college compared to 32.8% of students who opted out, an 8.3 percentage point difference and a 25.3 percent change – (41.1–32.8)/32.8 – in the relative probability.[11] Howell et al. (2021) also found that participating in Search was strongly associated with obtaining a BA in four years, particularly for sub-groups that were historically excluded from college.[12]

However, Jaquette & Salazar (2024) argue that student list products may exacerbate racial inequality in college access. The authors conceptualize student list products as "selection devices" (Hirschman & Bosk, 2020) that enable colleges to select which prospective students they target by incorporating search filters (e.g., high school graduating class, state). Norris (2021) defines "racialized inputs" as ostensibly race-neutral inputs that are systematically correlated with race because marginalized racial/ethnic groups have historically been excluded from the input (Norris, 2021). Jaquette & Salazar (2024) argue that several frequently utilized student list filters (e.g., zip code, AP test score, SAT score) meet the criteria of racialized inputs. Using a national sample of high school students and using data from actual student lists purchased by public universities, Jaquette & Salazar (2024) show that racialized search filters have a strong negative relationship with the selection of Black and Latinx prospects.

Because of the extent of residential segregation in the U.S., geographic borders are a commonly studied racialized input in scholarship about algorithmic bias (Benjamin, 2019; Harcourt, 2007; O'Neil, 2016). Student list products offer many geographic filters. Some geographic filters are

[11] Participating in Search was associated with a larger change in the relative probability of attending a 4-year college for Black students (24.5%) and Hispanic students (34.4%) than White students (21.6%), and a larger change for students whose parents did not attend college (40.6%) than those whose parents had a bachelor's degree (18.9%). Leveraging a natural experiment in College Board student list purchases, Smith et al. (2022) find that purchasing a prospect profile increases the probability that the student will apply to and enroll at the purchasing college, with larger effects for Black, Hispanic, and lowincome students.

[12] 20.6% of students who participated in Search obtained a BA in four years compared to 15.7% of students who opted out, representing a 31.2% (=(20.6-15.7)/15.7) increase in the relative probability of graduation. Furthermore, the relative increase in the probability of obtaining a BA was higher for Black (40.3%), Hispanic (43.3%), and Native American/Alaska Native students (48.3%) than it was for White (27.9%) and Asian (28.2%) students. The relative increase was also higher for students whose parents did not attend college (50.0%) than it was for students whose parents had a BA (25.3%).

based on known geographic borders (e.g., zip code, county, CBSA, state). College Board also created geographic borders that subsequently became filters in the *Student Search Service*, for example the Geodemographic Segment filters.[13] This manuscript focuses on Geomarkets. In their sample, Jaquette & Salazar (2024) found that 11% of student lists purchased by public research universities filtered on Geomarkets. Drawing from Norris (2021), we argue that geomarkets satisfy the two criteria of racialized inputs. First, they are ostensibly race-neutral inputs in that neither Zemsky & Oedel (1983) – nor subsequent EPS promotional material (e.g., College Board, 2011a) – mention race. Second, Geomarkets may be systematically correlated with race. For example, Geomarket "CA07" is "City of Oakland" and "CA08" is "Alameda Country, excluding Oakland." A university might purchase prospect contact information by filtering on CA08 in combination with additional filters, such as year of high school graduation and SAT test score. This article extends Jaquette & Salazar (2024) by examining how the racial composition of actual student list purchases changes if universities filter on particular Geomarkets.

Zemsky & Oedel (1983, pp. 42–44) discuss how the Market Segment Model and Geomarkets should be utilized in the context of purchasing student lists. The authors ask,

> Imagine for the moment that you recruit for a college that draws most of its students from regional or national segments. Where would you concentrate your energies? Ideally, you would seek communities [Geomarkets] with a high proportion of students already predisposed toward institutions such as your own. The Market Segment Model would provide this information through segment percentages for the community [Geomarket] in question. Further classification of students by social attributes allows you to identify a group for mailings or recruiting…If you were to recruit in Boston, only about two out of every ten students with fewer than two attributes would likely listen, while slightly less than half of the students with two or more attributes would be receptive…. Your efforts would surely be better directed toward …Manchester, Hartford, and Fairfield County …Indeed, in Fairfield County alone you could reach more than 40 percent of your "primary target" population – that is, students with a greater than 75-percent probability of concentrating their college choices among institutions like your own.

[13] Geodemographic segment filters utilize cluster analysis to allocate each census tract and each high school into different categories based past college enrollment and other factors (College Board, 2011b).

In both mailings and off-campus recruiting visits, Zemsky & Oedel (1983) recommend focusing on Geomarkets with large populations of students who are deciding between "institutions like your own" (p. 44). Selective colleges primarily draw from students in the "regional" and "national" segments. Zemsky & Oedel (1983) suggest that the student list purchases of selective colleges should focus on Geomarkets with large numbers of affluent, highly educated households. By contrast, the student list purchases of local state colleges and community colleges, which rely on enrollment from students in the "local" and "in-state," should focus on nearby Geomarkets with large numbers of low-SES students. Our analyses attempt to recreate the strategy recommended by Zemsky & Oedel (1983) by showing who is included/excluded when student list purchases filter on particular Geomarkets. Considering the correlation between race and wealth in segregated America, we suggest that a class-based list-buying strategy will increase racial stratification in college access. Furthermore, we anticipate that the students of color from affluent Geomarkets will tend to have college-educated parents and be enrolled in affluent, predominantly white schools.

4 Data and Methods

4.1 Data and Variables

RQ1. Our study utilizes two main data sources based on each research question. The first research question is focused on understanding the socioeconomic and racial variation between Geomarkets in metropolitan areas and how such variation changes over time. To answer this question, we use census tract data from the U.S. Census Bureau. Utilizing a small geographic area is important for implementing a spatial merge between Census data and Geomarket shape files (described below). Census tract is the smallest geographic area for which measures of both race/ethnicity and socioeconomic characteristics are available. Census tracts are statistical subdivisions of a county designed to capture relatively homogeneous demographic communities that are generally considered to be more accurate for population analyses than zip codes, which are spatial boundaries drawn to demarcate route efficiency for postal services [CITE] .

For the first research question, we use data from the 1980 and 2000 Decennial Census as well as 5-year estimates from the 2020 American Community Survey (ACS). For the 1980 Decennial Census, we specifically draw on Summary Tape File 1 (STF1) for variables about race and Hispanic origin collected via "short form" questions answered by all households and Summary Tape File 3 (STF3) for variables about socioeconomic characteristics (income, education, and poverty) collected via the "long form" questionnaire completed by a sample of households. The 1980 Decennial Census data collection period closely matches the data collection period of SAT score-sending behavior that Zemsky & Oedel (1983) utilized to create Geomarkets and the Market Segment Model. To examine how Geomarket characteristics change over time, we similarly use the Summary File 1A (SF1A) for census-tract measures of race and Hispanic origin and the Summary File 3A (SF3A) for census-tract measures of income, education, and poverty from the 2000 Decennial Census.[14] Beginning in 2010, the Decennial Census no longer collected a "long form" questionnaire. These questions were replaced by ACS. Therefore, we also utilized the 2020 5-year ACS for both race and socioeconomic characteristics at the census tract level, which includes data collected from 2016-2020.[15] This data collection period mirrors the period for our primary data collection about student list purchases used to analyze RQ2, as described below.

Across these data sources, we created measures of race and ethnicity, specifically the number and proportion of the census-tract population in the following categories: White, non-Hispanic; Black, non-Hispanic; Asian, non-Hispanic; Pacific Islander, non-Hispanic; American Indian and Alaskan Native, non-Hispanic; and two or more races, non-Hispanic. Measures of Asian, American Indian and Alaskan Native, two or more races, and Native Hawaiian and Pacific Islander (all non-Hispanic) were not available for the 1980 Decennial Census. We also created socioeconomic measures that approximate the predictors of market segment identified by Zemsky & Oedel (1983). These variables are median household income, percent of households below the poverty line, and people age 25+ with a BA. All measures were created at the census tract-level and the Geomarket-level by aggregating tract-level data to Geomarkets.

We assigned each census tract to College Board Geomarkets by implementing a partial spatial merge. Spatial manipulations utilized functions from the *sf* R package. Data to create the shapefiles for the College Board Geomarkets were obtained from a 2012 R-bloggers post.[16] Essentially, the data

[14]Data for the 1980 and 2000 Decennial Census were retrieved from the IPUMS National Historical Geographic Information System, created by Manson et al. (2024).

[15]Data for the 2020 5-year ACS were retreived from the tidycensus R package, created by Walker & Herman (2024)

[16]The author of the post reported that he found the zip codes associated with Geomarkets from a Google search.

file had one observation per zip code and a column that assigned each zip code to one Geomarket. Using these zip code-level data, we utilized the `aggregate()` function to create shapefiles for each Geomarket.

Next, we utilized the `st_intersection()` function to assign each census tract to a Geomarket, based on the intersection of their associated spatial shapefiles. Census tract shapefiles that intersected with multiple Geomarkets (i.e., a census tract's spatial boundaries were spread across two or more Geomarkets) broken into smaller shapefiles wholly contained within a single Geomarket. The variables in these shapefiles were then replaced with the original variable value multiplied by the proportion of land area of the census tract that was contained within the Geomarket. For a particular census tract, imagine that 60% of its land area was contained in Geomarket A, 40% of its land area was contained in Geomarket B, and the census tract reports 1,000 people who identify as Hispanic non-white. The partial spatial merge splits this census tract into two observations. The observation assigned to Geomarket A reports $.60 * 1000 = 600$ Hispanic non-white people and the observation assigned to Geomarket B reports $.40 * 1000 = 400$ Hispanic non-white people.

RQ2. Our study's second research question asks how does the racial and socioeconomic composition of included versus included prospects vary when student list purchases filter on Geomarkets. We answer this question using actual student lists purchased by public universities. In February 2020, we began issuing public records requests to public universities about student lists purchased from 2016 through 2020. We narrowed the scope of our request to student lists purchased from College Board, ACT, and the National Research Center for College and University Admissions (NRCCUA), the three largest student list vendors at the time. For each student list purchased from 2016 through 2020, we requested two related pieces of data: (1) the order summary, which specifies search criteria for the student list purchase; and (2) the de-identified prospect-level list produced from the search criteria.

The data collection sample for this project was all public universities in California, Illinois, Minnesota, and Texas. Utilizing public records requests to obtain public records is a painstaking process. Initially, the majority of universities did not respond or denied our request. Subsequently, we obtained pro bono representation from four law firms, which substantially increased the success of data collection. We also collected data from Arizona State University and Northern Arizona

University, because we were able to obtain pro-bono legal representation for these two universities. However, we were unable to obtain legal representation for Texas.

Even with firm representation, data collection remained difficult. Some universities provided records that were not usable for quantitative analyses (e.g., summary statistics across multiple orders; or data did not contain important fields). Some universities did not provide records based on legitimate legal grounds (e.g., data not in university possession; not required to create records that do not currently exist). We learned that many universities outsourced student list purchases to third-party consulting firms. Unfortunately, we were rarely able to obtain usable data from these universities. A small number of universities denied requests based on potentially questionable legal rationale, but we lacked the resources to litigate.

The primary data source for our second research question is therefore student lists purchased from College Board for which we received both (a) the order summary data and (b) the de-identified prospect-level student list data. This sample includes a total of 414 orders associated with 2,549,085 prospects made by 14 [KS CHECK THIS] public universities located in California, Illinois, Minnesota, and Arizona [KS Does this still apply?]. Although these lists were purchased by individual universities, the set of prospects included in each list is a function of the search criteria specified for that student list purchase.[17] The resulting student lists could hypothetically extend to any university placing student lists orders based on the same filter criteria. In other words, any observed patterns in the findings below would remain constant for any university selecting the same filters. Therefore, we utilize these data not to analyze the behavior of individual universities, but to identify which prospective students are included when a particular set of search criteria are selected.

In particular, we answer the second research question by analyzing particular student list purchases that did *not* utilize the Geomarket search filter, but did purchase prospects from all Geomarkets in a particular metropolitan area. For each prospect we know their home zip code and, therefore, which Geomarket they belong to. We therefore simulate which prospective students would have been included or excluded from the student list purchase had the purchase filtered on particular Geomarkets.

[17]ADD CAVEAT THAT PURCHASES EXCLUDE PROSPECT PROFILES THAT WERE PREVIOUSLY PURCHASED

The variables of interest for student list data are the characteristics of prospects who would have been included versus excluded by our simulations by Geomarket filter. Prospect characteristics are derived from the pretest questionnaire administered to College Board test-takers that are included in the de-identified student lists we received (e.g., HS code, HS GPA range, intended major). College Board asks students separate questions about ethnicity (Cuban, Mexican, Puerto Rican, other Hispanic, non-Hispanic, ethnicity nonresponse) and race (American Indian or Alaska Native, Asian, Black, Native Hawaiian or other Pacific Islander, White, race non-response), allowing students to check as many boxes as they want (College Board, 2016). From these responses, a College Board "derived aggregate race/ethnicity" was re-created based on the U.S. Department of Education reporting guidelines that includes the following categories: no response; American Indian/Alaska Native; Asian; Black; Hispanic/Latino; Native Hawaiian or Other Pacific Islander; White; other; two or more races, non-Hispanic (College Board, 2016).[18] Information about student socioeconomic status is limited. However, we create a measure of whether the prospect is first-generation college student based on their parents' level of education that was self-reported on the College Board questionnaire [KS double check this].

4.2 Methods

Research design. We utilize a multiple, quantitative case study design in which metropolitan areas are cases. Case studies are used to gain a deeper understanding of the phenomenon of interest by comparing and contrasting across different settings [CITE YIN 2001]. Our study's research questions explore the socioeconomic and racial variation between Geomarkets, how such variation changes over time, and how Geomarket landscapes shape the composition of included versus excluded prospects. Our goal is not to generalize Geomarket variation nationally, but rather to explore how differences across Geomarket landscapes shape prospect pools based on the geographical model of metropolitan areas and their demographic characteristics. Such aims align with the purpose of case studies, which drive the exploration of research questions focused on the "how" and "why" of phenomenon in rich and nuanced contexts. We therefore focus on minimizing the number of metropolitan areas in order to provide sufficient analytic depth while situating each case within

[18]Any student who selects a Hispanic ethnicity category is defined as Hispanic/Latino, regardless of the race categories they select. Additionally, non-Hispanic students who check "American Indian or Alaska Native" and another race group are defined as "two or more races, non-Hispanic."

its specific historic and contemporary sociodemographic characteristics [TIE IN THEORETICAL FRAMEWORK HERE A BIT MORE]. Online Appendix XXX presents results for a larger number of metropolitan areas.

Case selection was therefore informed by purposeful sampling to identify "information-rich" cases (Patton, 2002; Yin, 2009) that can provide in-depth knowledge about variation across Geomarkets and overtime. We considered metropolitan areas as information rich cases across three broad dimensions: 1) urban model structures, 2) geographical variation, 3) variation across racial/ethnic and socioeconomic characteristics, and 4) availability of student list orders and de-identified list data. Based on our read of Zemsky & Oedel (1983), we identified classic urban model structures that reflected "major metropolitan area[s] …composed of several markets, usually corresponding to the inner city, a first ring of suburbs, and an outer ring of suburbs" (p. 11-12), such as Boston, Chicago, Detroit, Baltimore, Denver, Houston, Miami, Philadelphia, Phoenix, and Pittsburgh. To compare and contrast with classic urban model structures, we also identified alternative urban models such as bimodal or metroplex models that contain two centralized cores surrounded by the more classing suburban ring (e.g., Dallas-Fort Worth and San Francisco) and multi-nuclei models where urban growth develops around multiple, sometimes uncentralized and independent, metropolitan areas (e.g., Los Angeles and New York City). The third consideration addresses geographical variations in demographic populations by intentionally selecting metropolitan cases across different U.S. regions (West, Midwest, Northeast, South) to ensure resident and prospect pools mirror broader populations. Cumulatively related to all previous selection dimensions, we are also interested in variation of racial and socioeconomic populations between Geomarkets within a metropolitan areas (RQ1) and how such variation shapes which prospective students are targeted by student list purchases (RQ2). We therefore considered whether or not metropolitan areas provided sufficient and varied racial and socioeconomic diversity for our research purposes.

Lastly, choice of metropolitan cases was informed by student list data availability. Although Census data are available for all metropolitan areas nationally (RQ1), we do not have good candidate student list data for all metropolitan areas (RQ2). In order to simulate which prospective students would have been included or excluded from the student list purchase had the purchase filtered on particular Geomarkets, student list data must contain orders that resulted in a large pool of prospects within the metropolitan areas considered above that would include all Geomarkets within metropolitan areas. This lead us to select on orders that filtered for an entire state (e.g., State filter is set to Pennsylvania), an entire metropolitan area without a Geomarket filter (CBSA filter is set to the Philadelphia metropolitan area) , or an entire metropolitan area with a Geomarket filter inclusive of all Geomarkets (CBSA filter is set to the Philadelphia metropolitan area and Geomarket filter is set to all five Geomarkets in the Philadelphia area). In order to isolate the impact of Geomarkets on the racial/ethnic and socioeconomic characteristics of prospect pools, a suitable metropolitan case candidate would also be contingent on student list orders that did not include too many filtering criteria beyond those detailed previously. Because nearly all orders we collected (Author, BLINDED) filter on some academic criteria, we only considered orders that included assessment threshold filters (e.g., PSAT, SAT) across a wide score range to explore whether and to what extent Geomarket contributions to prospect pools are consistent across all score ranges.

Our case selection process resulted in three metropolitan cases: Chicago, Dallas-Fort Worth, and Los Angeles.

Analyses. Analyses are simultaneously descriptive and spatial. We answer RQ1 by producing Geomarket-level tables and graphs that show how the Geomarkets in a selected metropolitan area vary on racial and socioeconomic characteristics and how they vary over time. We also produce interactive maps at the census tract-level to show more granular variation within and between Geomarkets.

We answer RQ2 by analyzing student list purchases that encompassed all Geomarkets in a selected metropolitan areas. Descriptive tables and graphs describe the racial and socioeconomic characteristics of prospects that would have been included/excluded had the purchase filtered on particular Geomarkets. We also create interactive maps of prospect pools by Geomarket contributions to provide a more granular visualization of analyses.

5 Findings

5.1 Chicago

Shifting Demographics, Persistent Segregation in Geomarket Landscape

Figure 2 presents the seven Geomarkets in the Chicago metropolitan area by total population across the three census periods. The maps in the figure show how Chicago Geomarkets reflect the classic urban geographical structure of an inner-city core surrounded by a ring of suburbs as described by Zemsky & Oedel (1983) in the development of The Market Segment Model. Based on the color gradient scale representing total population density, Figure 2 indicates northern suburb Geomarkets in the metropolitan area - Chain of Lakes, Northwest Suburbs, Northshore, Evanston and Skokie - experienced relatively little population growth from 1980 through 2020. In contrast, the most significant population increases occured in the Western Suburbs (1.2 Million to 1.6 Million) and the South and Southwest Suburbs (less than 1 Million to 1.3 Million) Geomarkets. The City of Chicago Geomarket, forming the metropolitan area's central core, was the only locality to experience a population decline, from 3.1 Million in 1980 to 2.8 Million in 2020, despite remaining the most densely populated Geomarket.

These population shifts have contributed to changes in the racial/ethnic composition within and across Geomarkets over time. Figure 3 illustrates the racial and ethnic composition of each Geomarkets across the three census periods. In 1980, nearly all Geomarkets were predominantly White, with proportions ranging from 83% in the South and Southwest Suburbs to approximately 93% in North Shore. In contrast, the City of Chicago had a substantially more diverse population, with White residents comprising only 46% of its total population. By 2020, several Geomarkets that were previously predominantly White shifted to a more balanced racial/ethnic distribution, including Chain of Lakes (59% White, 8% Black, 24% Hispanic; 7% Asian Pacific Islander), Northwest Suburbs (62% White, 3% Black, 18% Hispanic; 15% Asian Pacific Islander), Evanston and Skokie (64% White, 7% Black, 10% Hispanic; 16% Asian Pacific Islander), Western Suburbs (56% White, 9% Black, 23% Hispanic; 9% Asian Pacific Islander), and South and Southwest Suburbs (53% White, 24% Black, 18% Hispanic; 3% Asian Pacific Islander). For many Geomarkets, this balance in racial/ethnic composition was the result of large increases in the Latinx population from 1980 to

2020, which ranged from a 7 percentage point increase for the Evanston and Skokie Geomarket to a 19 percentage point increase for Western Suburbs. Some Geomarkets also experienced a substantial increase in Black populations (South and Southwest Suburbs) and in Asian populations (Northwest Suburbs and Evanston and Skokie).

Figure 3 also indicates that, although the North Shore and City of Chicago Geomarkets underwent some changes in racial and ethnic composition, their overall demographic patterns remained relatively the same across the three census periods. For instance, North Shore experienced some increases in Hispanic (2% in 1980 to 8% in 2020), Asian Pacific Islander (7% in 2000 to 10% in 2020), and Black (2% in 1980 to 3% in 2020) populations yet remained a predominantly White Geomarket (74% in 2020). City of Chicago also experienced relatively modest declines in its Black population (37% in 1980 to 33% in 2020), alongside increases in its Hispanic (15% in 1980 to 26% in 2020) and Asian Pacific Islander populations (4% in 2000 to 6% in 2020), further substantiating the Geomarket as the most racially/ethnic diverse in the metropolitan area.

We also explore socioeconomic demographics - median income, percent living below poverty, and educational attainment - within and across Geomarkets over time in Figure 4. Overall, median income both within and across Geomarkets in the Chicago metropolitan area remained relatively stable across the three census periods. For instance, in 1980, median household income across the Chicago metropolitan area ranged from a high of $158,000 in the North Shore Geomarket to a low of $66,000 in the City of Chicago Geomarket. However, median incomes in all other Geomarkets were closer to the upper thresholds of affluence, such as $120,000 in the Northwest Suburbs, $119,000 in Evanston and Skokie, $108,000 in Chain of Lakes, $105,000 in the Western Suburbs, and $99,000 in the South and Southwest Suburbs. While overall income patterns across Geomarkets remained consistent through 2020, a median income increase for the City of Chicago Geomarket ($79,000) and decrease in the South and Southwest Suburbs Geomarket ($93,000) narrowed the income gap between the lowest and second-lowest Geomarkets to just $14,000.

Figure 4 also shows that from 1980 to 2020, the percentage of residents living in poverty declined in the City of Chicago Geomarket while it increased in all other Geomarkets, resulting in a narrowing of poverty gaps across the Chicago metropolitan area. Similar patterns are evident in educational attainment across Geomarkets. In 1980, the City of Chicago had the lowest percentage of residents with a bachelor's degree or higher (13%). However, by 2020, the Geomarket experienced the largest percentage point increase in college degree attainment, reaching 38%. In comparison, all other Geomarkets experienced smaller gains in the share of residents with a bachelor's degree or higher over the same period. These trends contributed to a narrowing of the educational attainment gap across Geomarkets from 1980 to 2020.

From 1980 to 2020, these demographic shifts have transformed the Chicago metropolitan area's Geomarket landscape from largely a binary structure into a more tiered dynamic shaped by racial/ethnic and socioeconomic characteristics. The original Geomarket boundaries delineated significant racial and income segregation in the 1980s. This included Black, Hispanic, and Asian residents primarily in the City of Chicago Geomarket and White residents in Geomarkets forming the suburban ring of the metropolitan area. Income, poverty, and educational attainment also created a static socioeconomic divide in 1980, with southern Geormarkets (City of Chicago and South and Southwest Suburbs) characterized by lower affluence and educational attainment compared to the higher socioeconomic standing of the northwestern suburbs. However, declining White populations, Hispanic and Asian population growth, and Black outmigration, as well as some narrowing of education and poverty gaps, have contributed to a more stratified Geomarket dynamic in the metropolitan area despite significant disparities remaining. The City of Chicago Geomarket remains the critical geographical hub across all Geomarkets for racial/ethnic diversity; however, other Geomarkets include substantive numbers of residents across racial/ethnic groups (such as South and Southwest Geomarket for Black residents, Chain of Lakes for Hispanic residents, and Northwest Suburbs for Asian residents) while the the Evanston and North Shore Geomarkets remain predominantly White. While some stark socioeconomic gaps within Geomarkets have narrowed since 1980, significant geographical income segregation remains across Geomarkets despite a more clearly defined middle-to-high socioeconomic Geomarket group (Chain of Lakes, Northwest Suburbs, Western Suburbs).

Composition of Students Lists by Geomarket Contributions

To examine how the socioeconomic and racial composition of included versus excluded prospects varies when student list purchases filter on particular Geomarkets, we analyze six orders placed by a research university targeting prospects across the entire state of Illinois. Two of these orders applied the same filters: SAT score thresholds ranging from 1020 to 1150, GPA ranging from B- to A+, and high school class targeting students from the 2019-2020 and 2020-2021 graduating classes, respectively. The remaining four orders used similar GPA and high school class filters but differed in SAT thresholds- two targeted students with relatively middle-range scores (1160 to 1300) and two targeted those with relatively high scores (1310 to 1600). Because all six orders included an Illinois state filter, we can utilize prospects from the Chicago metropolitan area within the resulting student lists to examine Geomarket contributions by simulating the application of a Geomarket filter across low-, middle-, and high-range SAT threshold orders.

Figure 5 presents the racial/ethnic composition of purchased student profiles within Geomarkets in the Chicago metropolitan area. At the lowest PSAT score thresholds (top panel, 1020-1150) the racial/ethnic distribution of prospects within Geomarkets generally reflects the demographic makeup of the metropolitan area in 2020 (see Figure 3). For example, more than 8,000 of the 16,485 total prospects in this SAT range order were concentrated in the Western Suburbs (56% White, 8% Asian, 6% Black, 26% Hispanic, 4% Multiracial) and South and Southwest Suburbs (55% White, 3% Asian, 17% Black, 22% Hispanic, and 3% Multiracial), both of which yield prospect pools comparable to the racial/ethnic makeup of their overall Geomarket populations. Similar to the larger metropolitan area, the Northshore (78% White, 8% Asian, 2% Black, 8% Hispanic) and the Northwest Suburbs (61% White, 11% Asian, 2% Black, 23% Hispanic) Geomarket pools exhibit the greatest proportions of White prospects, reflecting the Geomarket dynamics in the metropolitan area population although they yielded fewer overall students. Interestingly, while the City of Chicago is the most racially/ethnically diverse Geomarket in the larger metropolitan area, its prospect pool in Figure 5 includes nearly double the proportion of Hispanic (50%) prospects relative to the larger Geomarket resident population (26% Hispanic) in Figure 3 with a lower proportion of White prospects (14%).

However, the racial/ethnic composition of prospect pools become less similar to the overall metropolitan area as PSAT scores increase. Notably, the shares of White and Asian prospects within Geomarkets increase, while Black and Hispanic prospects decrease. For instance, Asian prospects over representation in Geomarkets relative to the overall resident population at the

1310-1600 SAT score threshold ranges from a minimum of 4 percentage points in the North Shore Geomarket (17% of prospects versus 13% of residents) to a maximum of 21 percentage points in the Chain of Lakes (28% of prospects versus 7% residents) Geomarket. The City of Chicago Geomarket exhibits the largest underrepresentation of Black prospects (7% of prospects versus 33% of residents) while Chain of Lakes exhibits the largest underrepresentation of Hispanic prospects (7% of prospects versus 24% of residents).

We also explore contributions across Geomarkets to overall prospect pools by race/ethnicity. For instance, Figure 6 shows the contributions of each Geomarket to the pool of prospects from the two orders targeting middle range SAT scores (1160-1300) by race/ethnicity. The top panel presents the full distribution of the 13,643 total prospects (whose race/ethnicity is known) included in these orders by Geomarkets: 11% reside in Chain of Lakes, 13% in Northwest Suburbs, 5% in North Shore, 5% in Evanston and Skokie, 17% in City of Chicago, 28% in Western Suburbs, and 20% in South and Southwest Suburbs. These overall distributions are compared to those in the lower panels of Figure 6, which illustrate the proportional representation of each race/ethnicity group across Geomarkets.

More than half (n=8,256) of all prospects whose contact information was purchased in these middle SAT score orders identified as White. Figure 6 shows nearly all Geomarkets contributed to the pool of White prospects at rates nearly proportional to their overall contributions to all included prospects. One exception is the City of Chicago Geomarket, which contributed only 7% of White prospects, despite accounting for 17% of all included prospects. On the other hand, Western Suburbs and South and Southwest Suburbs Geomarkets 32% and 23% of White prospects while only accounting for 28% and 20% of all included prospects, respectively. Similar patterns are observed for Asian students, with proportional contributions by Geomarket largely consistent with thier overall distribution, except for Northwest Suburbs (19% versus 13% for all prospects), Evanston and Skokie (10% versus 5% for all prospects) contributing disproportionately larger shares and the South and Southwest Suburbs (8% versus 10% for all prospects) contributing smaller shares relative to their overall contribution to the larger prospect pool.

In contrast, these representational patterns are reversed for Black and Hispanic prospects in Figure 6. Among the nearly 1,000 Black students included in these orders, the City of Chicago and

South and Southwest Suburbs contributed disproportionately higher shares, 48% and 30%, respectively, compared to their overall contributions of 17% and 20% of all included prospects, whereas all other Geomarkets contributed substantially smaller proportions of Black prospects. The City of Chicago Geomarket also contributed larger shares of the nearly 3,000 Hispanic students (39% versus 17% for all prospects), while all other Geomarkets contributed comparable or relatively smaller proportions of Hispanic prospects than their overall representation among all included prospects.

Appendix figures @fig-chicago-rq2-midSAT-race and **?@fig-chicago-rq2-highSAT-race** similarly depict Geomarket contributions for pools of prospects resulting from orders targeting lower-range (1020-1150) and high-range (1310-1600) SAT scores. Both figures demonstrate how representational Geomarket contributionsacross race/ethnicity, such as City of Chicago disproportionately contributing larger shares of Black and Hispanic prospects, remain consistent even at lower and higher SAT score thresholds.

We also examine the contributions of each Geomarket to the pool of prospects based on first-generation college student status. Similar to race/ethnicity figures above, Figure 7 presents the Geomarket distribution for the 13,749 total prospects (whose first-generations status is known) included in middle-range SAT score orders (1160-1300). Among the 1,743 prospects whose parents did not attend college ("no college"), the City of Chicago stands out as the only Geomarket contributing a disproportionately larger share of first-generation college students - 38% in comparison to 17% for all included prospects in this SAT range. In contrast, all other Geomarkets contributed disproportionately smaller shares of first-generation college students whose parents did not attend college relative to all included prospects, with such disparity ranging from a one-percentage-point difference (South and Southwest Suburbs) to a nine-percentage-point difference (Western Suburbs). For prospects whose parents attended some college but did not complete their degrees ("some college"), Figure 7 indicates both City of Chicago and South and Southwest Suburbs Geomarkets contribute a disproportionately larger share of first-generation students. These representational patterns are reversed among prospects that are not first-generation college students. The City of Chicago Geomarket contributed a substantially smaller share of not-first generation prospects (12%) relative to all prospects (17%) in this SAT range, whereas all other Geomarkets contributed comparable shares.

Relative to Figure 7, appendix figures @fig-chicago-rq2-midSAT-ses and **?@fig-chicago-rq2-highSAT-ses** demonstrate Geomarket contribution patterns by first-generation college student status are less pronounced in low-SAT range orders (1020-1150) and more pronounced in high-range SAT orders (1310-1600), respectively.

Finally, we examine Geomarket contributions to prospect pools by both first-generation college student status and race/ethnicity in the Chicago metropolitan area. Figure 8 presents the Geomarket distribution of the 12,981 total prospects (whose first-generation status and race/ethnicity is known) included in middle-range SAT (1160-1300) orders. For instance, among all White prospects (n=8,155) whose contact information was purchased in this SAT score range, approximately 6% were first-generation college students whose parents did not attend college, 15% were first-generation college students whose parents attended some college but did not complete their degree, and 79% were not first-generation college students. Figure 8 shows the City of Chicago and South and Southwest Suburbs Geomarkets disproportionately contribute larger shares of White first-generation college students who parents did not attend college (10% and 9%, respectively). For first-generation college students whose parents attended some college but never completed degrees, only the South and Southwest Suburbs (25%) Geomarket contributed a substantially larger share of White prospects. In contrast, Geomarkets such as Chain of Lakes (82%), North Shore (94%), Evanston and Skokie (81%), and Western Surburbs (84%) contribute a disproportionately larger share of White prospects who are not first-generation college students.

Figure 8 indicates these Geomarket patterns persist across other racial/ethnic categories. The City of Chicago Geomarket consistently contributed a disproportionately large share of first-generation college students whose parents did not attend college across all racial/ethnic categories. However, the magnitude of this disproportionality varied- from a 1-percentage-point difference for Black prospects to a 23 percentage-point difference for Asian prospects. Among Hispanic students, contributions to the first-generation prospect pool were notably balanced across Geomarkets, with the exception of North Shore and Evanston and Skokie Geomarkets, which contributed substantially lower shares of first-generation Hispanic students. Although Asian and Black prospects who are not first-generation college students make up a relatively smaller portion of the overall pool, Figure 8 suggests that such prospects are primarily contributed by the Chain of Lakes, North Shore, Evanston and Skokie, and Western Surburbs Geomarkets. Appendix figures **?@fig-chicago-rq2-lowSAT-combo** and @fig-chicago-rq2-highSAT-combo show the magnitude of these Geomarket contribution disparities become more pronounced at as SAT score thresholds increase.

The enduring segregated structure of the Chicago metropolitan area from 1980 to 2020 analyzed above plays a significant role in how Geomarkets shape the racial/ethnic and socioeconomic composition of prospect pools. Reflecting the larger metropolitan area dynamics, central Geomarkets that are predominantly comprised of low-income communities of color such as the City of Chicago and South and Southwest Suburbs consistently contribute disproportionately larger shares of Black, Hispanic, and first-generation college prospects, especially at lower SAT score thresholds. On the other hand, predominantly White and affluent Geomarkets in the suburban ring of the metropolitan area like the Chain of Lakes, North Shore, and Evanston and Skokie contribute larger proportions of White and Asian prospects, as well as non-first generation college students. However, the City of Chicago stands out in playing crucial role in fostering college access for first-generation Asian college students, contributing such prospects to the overall pool at significantly higher, disproportionate rates than any other Geomarket.

5.2 Dallas-Fort Worth

Suburban Geomarket Growth Eases Racial Disparities, Concentrated Wealth Persists

The six Geomarkets within the Dallas-Fort Worth metropolitan area are illustrated in Figure 9 by total population across the three census periods. The Dallas-Fort Worth region represents a unique "metroplex" case formed by the convergence of two separate metropolitan areas, which creates a unique urban spatial structure that differs from the classic urban core and suburban ring model showcased by Chicago. As depicted in Figure 9, two distinct inner-core Geomarkets (City of Dallas and City of Fort Worth) are seperated by a centrally located suburban Geomarket encompassing Irving, Arlington, & Grand Prairie. These central Geomarkets are surrounded by the more conventional outer ring of suburban Geomarkets (Dallas County, Collin and Rockwall Counties, and West of Dallas/Ft. Worth Metroplex).

From 1980 to 2020, the population of the overall Dallas-Fort Worth metropolitan area increased substantially from approximately 2.7 Million to 6.8 Million. Figure 9 showcases all six Geomarkets experienced population growth over the three census periods. However, the most pronounced increases occured in the West of Dallas/Fort Worth Metroplex and Collin & Rockwall Counties Geomarkets, which grew from approximately 340,000 to 1.4 Million and 170,000 to 1.2 Million, respectively. These population trends, as shown in Figure 9, suggest population growth has been partly driven by urban sprawl from the metropolitan centers - City of Forth Worth and City of Dallas - into the surrounding suburban and rural areas of the metropolitan areas. This outward expansion may also account for the comparatively larger geographic size of the West of Dallas/Fort Worth Metroplex Geomarket from 1980 to 2000.

Figure 10 presents the racial and ethnic composition of each Geomarket within the Dallas-Fort Worth metropolitan area across the three census periods. In 1980, all Geomarkets were predominantly White, with White populations ranging from 62% in City of Dallas to nearly 92% in West of Dallas/Fort Worth Metroplex. By 2000, however, Geomarkets located in the central part of the metropolitan area exhibited a more balanced racial/ethnic distribution, including Dallas County (58% White, 16% Black, 19% Hispanic; 6% Asian Pacific Islander), Irving, Arlington, and Grand Prairie (54% White, 12% Black, 26% Hispanic; 16% Asian Pacific Islander), and City of Fort Worth (57% White, 16% Black, 22% Hispanic; 3% Asian Pacific Islander). In contrast, Collin & Rockwall Counties and West of Dallas/Fort Worth Metroplex Geomarkets remained predominantly White in 2000 at 78% and 80%, respectively. Notably, by 2000, the City of Dallas was no longer a predominantly White Geomarket, with a racial/ethnic composition of approximately 24% Black, 30% Hispanic, and 3% Asian Pacific Islander residents.

These shifts in racial and ethnic composition within and across Geomarkets became more pronounced between 2000 and 2020. The Collin and Rockwall and West of Dallas/Fort Worth Metroplex Geomarkets experienced continued declines in their share of White residents. However, both Geomarkets remained predominantly White (58% and 63%, respectively). In contrast, all other Geomarkets experienced continued increases in the shares of Black and Hispanic residents, resulting in a diminished previously White-majority populations for Dallas County (33% White, 23% Black, 32% Hispanic; 9% Asian Pacific Islander), Irving, Arlington, and Grand Prairie (30% White, 20% Black, 36% Hispanic; 12% Asian Pacific Islander), and City of Fort Worth (46% White, 15% Black, 33% Hispanic; 4% Asian Pacific Islander). Lastly, continuous increases in the shares of Black and

Hispanic residents further diversified the City of Dallas, making it the most racially/ethnically diverse Geomarket in the Dallas-Fort Worth metropolitan area.

Socioeconomic demographics of median income, percent living below poverty, and educational attainment over time are presented in Figure 11 for the Dallas-Fort Worth metropolitan area. Overall, median income both within and across Geomarkets remained relatively stable across the three census periods. Between 1980 to 2000, affluence levels across Geomarkets were consistent, ranging from a low of $82,000 in City of Fort Worth to a high of $135,00 in the Collin & Rockwall Counties Geomarket. However, the substantial increase in median income for the Collin & Rockwall Counties Geomarket during this time period plateaued by 2020, reshuffling relatively affluence levels among Geomarkets. By 2020, Collin & Rockwall Counties remained the most affluent Geomarket with a median household income of $133,000, followed by West of Dallas/Fort Worth Metroplex ($116,000), and Dallas County ($90,000). In contrast, median household income for City of Dallas and City of Fort Worth remained relatively stable and continued to rank at the lower levels of affluence within the metropolitan area. [KS: NEED TO CHECK THIS; I THINK CITY OF DALLAS AND CITY OF FORT WORTH ARE MIXED UP BETWEEN GRAPH VERSUS TABLE]

Figure 11 also illustrates changes in the percentage of residents living in poverty within Geomarkets over time, revealing shifting dynamics across Geomarkets similar to those observed in median household income. In 1980, poverty rates were comparably low in both Collin & Rockwall Counties and Dallas County, moderate in the Irving, Arlington, and Grand Prarie and West of Dallas/Fort Worth Metroplex Geomarkets, and highest for City of Dallas and City of Fort Worth Geomarkets. Overtime, poverty rates declined in Collin & Rockwall Counties and West of Dallas/Fort Worth Metroplex, while increasing for all other Geomarkets. These divergent trends resulted in a widening gap in poverty levels across the Dallas-Fort Worth metropolitan area. A similar widening disparity is evident in educational attainment. Although all Geomarkets experienced increases in the percentage of residents with a bachelor's degree or higher between 1980 and 2020, the Collin & Rockwall Counties Geomarket experienced a substantially greater increase - from 23% in 1980 to 50% in 2020- maintaining the gap with other Geomarkets in terms of educational attainment.

The Dallas-Fort Worth metroplex experienced substantial demographic growth since Geomarket boundaries were dilineated by Zemsky & Oedel (1983) in the early 1980s. While all six Geomarkets experienced population increases, the most significant growth occurred in the outer suburban areas, reflecting ongoing urban sprawl. Such growth is largely attributed to increases in Hispanic, Black, and Asian populations leading to only two of the six Dallas-Fort Worth Geomarkets remaining predominantly White (Collin and Rockwall Counties and West of Dallas/Fort Worth Metroplex. On the other hand, the metropolitan area has experienced widening disparities in income, poverty, and education attainment across Geomarkets, especially between the historically affluent Collin and Rockwall Counties and the less economically advantaged inner-core Geomarkets (City of Fort Worth and City of Dallas). Together, these trends underscore the growingly racial/ethnic diverse but widening economic inequality within the evolving Geomarket landscape of the Dallas-Fort Worth metroplex.

Composition of Students Lists by Geomarkets

We also analyze student list orders collected through public requests to assess how the racial/ethnic and socioeconomic composition of included versus excluded prospects varies when filtering on particular Geomarkets within the Dallas-Fort Worth metropolitan area. Specifically, we analyze three list orders placed by a research university targeting prospects across 87 different Geomarkets nationwide, including all six Geomarkets in the Dallas-Fort Worth Metropolitan area. Each order also filtered for prospects in the 2019-2020 graduating class and based on PSAT scores across three ranges: 1070-1180, 1190-1260, and 1270-1520. Similar to Chicago analyses, we focus on prospects within the middle PSAT score range (1190-1260) from the Dallas-Fort Worth metropolitan area to simulate Geomarket contributions and assess patterns of inclusion versus exclusion.

Figure 12 presents the racial/ethnic composition of purchased student profiles within Geomarkets in the Dallas-Forthworth area. At the lowest PSAT score thresholds, notable differences emerge in the racial/ethnic composition of prospects within Geomarkets when compared to the overall demographic makeup of the metropolitan area in 2020 (see Figure 10). For example, the largest number of prospects in the 1070-1180 PSAT range were from the Collin & Rockwall Counties (57% White, 7% Black, 17% Hispanic, 14% Asian) and West of Dallas/Forth Worth Metroplex Geomarkets (61% White, 7% Black, 19% Hispanic, 7% Asian), both of which yield predominantly White prospect pools. On the other hand, the Dallas County (36% White, 17% Asian, 15% Black, 28% Hispanic) and the Irving, Arlington, and Grand Prairie (34% White, 13% Asian, 15% Black, 34% Hispanic) Geomarket pools have the greatest proportions of non-White prospects (although yielding fewer overall students). Interestingly, while the City of Dallas is the most racially/ethnically diverse Geomarket in the larger metropolitan area, its prospect pool in Figure 12 includes larger proportion of Hispanic (41%) prospects but lower proportions of Asian (4%) and Black (9%) students comparatively.

These racial/ethnic composition patterns shift as PSAT scores increase. Shares of White prospects within Geomarkets remain relatively proportional to the overall 2020 metropolitan distribution in Figure 10. However, prospect pools within Geomarkets from the middle range PSAT score (1190-1260) to the high PSAT score range (1270-1520) become disproportionately more Asian, while the representation of Hispanic and Black prospects decline substantially.

Figure 13 presents the race/ethnicity of all prospects targeted in the middle PSAT score range across Geomarket contributions. Figure 13 shows nearly all Geomarkets contributed to the pool of White prospects at rates nearly proportional to their overall contributions to all included prospects, with the exception of the West of Dallas/Fort Worth Metroplex Geomarket contributing a disproportionately larger share (29% versus 23% for all prospects). Larger disparities across Geomarket contributions were evident for Asian, Black, and Hispanic students. The Dallas County (20% versus 13% for all prospects) and Colin and Rockwall Counties (47% versus 37% for all prospects) Geomarkets contributed a disproportionate larger share of Asian students, whereas nearly all other Geomarkets contributed disproportionately smaller shares.

Representational patterns across Geomarkets are reversed for Black and Hispanic prospects in Figure 13. All Geomarkets besides Collin and Rockwall Counties and West of Dallas/Fort Worth Metroplex contributed equal or larger proportions of Black and Hispanic prospects relative to their contributions to the overall prospect pool in the Dallas-Fort Woth metropolitan area. However, the City of Dallas Geomarket contributed the largest disproportionate share of Hispanic prospects (19% versus 11% for all prospects), whereas the Dallas Counties Geomarket contributed the largest disproportionate share of Black prospects (21% versus 13% for all prospects).

Contributions of each Geomarket to the pool of prospects based on first-generation college student status from the Dallas-Fort Worth metropolitan area are presented in Figure 14. Only 303 prospects of the 3,928 total in this middle PSAT score range pool were first-generation college students whose parents did not attend college. Again, all Geomarkets besides Collin and Rockwall Counties (14% versus 36% for all prospects) and West of Dallas/Fort Worth Metroplex (15% versus 24% for all prospects) contributed equal or larger proportions of first-generation college students (no college) relative to their contributions to the overall prospect pool. Disproportioantely larger contributions range from six percentage points by the Dallas Counties Geomarket (19% versus 13% for all prospects) to 11 percentage points by the City of Dallas Geomarket (22% versus 11% for all prospects). Contributions become more proportional for the pool of first-generation college students whose parents attended but did not complete their degree. Proportional balances across Geomarkets are also evident for the 3,069 prospects that are not first-generation college students, with the exception of Collin and Rockwall Counties Geomarket contributing the largest disproportinate share of not first-generation college students (40%) relative to the contributions to the overall prospect pool (36%).

Lastly, Figure 15 presents Geomarket contributions to prospect pools by both first-generation college student status and race/ethnicity in the Dallas-Fort Worth metropolitan area. Among all White prospects (n=2,094) whose contact information was purchased in this middle PSAT score range, approximately 3% were first-generation college students whose parents did not attend college, 11% were first-generation college students whose parents attended some college but did not complete their degree, and 86% were not first-generation college students. Figure 15 shows nearly all Geomarkets contribute a nearly proportionate share of prospects by first-generation college students relative to the overall pool. The only exception is the Irving, Arlington, & Grand Prairie Geomarket contributing a relatively larger share of White first-generation college students whose parents attended some college but did not complete their degree (21% versus 11% for all prospects).

Similar patterns of one or two Geomarkets disproportionately contributing larger shares of first-generation college students was evident across other racial/ethnic categories in Figure 15. For instance, City of Dallas (18%) and City of Fort Worth (24%) contributed larger proportions of first-generation college students whose parents did not attend college relative to the overall pool of all prospects (8%). On the other hand, the Irving, Arlington, & Grand Prairie (23%) and Dallas

Counties (26%) Geomarkets contributed disproportionately larger proportions of Black students whose parents attended some college but did not complete their degree relative to the overall pool of all prospects (17%). For Asian prospects, City of Fort Worth and Irving, Arlington, & Grand Prairie Geomarkets contributed disproportionately larger shares of first-generation college students across both parents with no college and some college. City of Dallas (38%), City of Fort Worth (39%), Irving, Arlington, & Grand Prairie (32%), Dallas Counties (28%) all contributed larger shares of Hispanic students whose parents did not attend college relative to the overall prospect pool of these first-generation college students (23%), whereas only Dallas Counties contributed to larger shares of Hispanic students who parents attended some college but did not attain their degree (26% versus 20% for all prospects).

Analyses of student list orders across the Dallas-Fort Worth metropolitan area reveals patterns of racial/ethnic and socioeconomic stratification in Geomarket contributions. As Dallas-Fort Worth became increasingly diverse from 1980 to 2020, a more balanced racial/ethnic distribution emerged across the metropolitan area's Geomarket landscape. However, these patterns did not translate to racial/ethnic composition of student prospect pools. Suburban Geomarkets like Collin and Rockwall Counties and the West of Dallas/Fort Worth Metroplex yielded a disproportionately larger share of Asian prospects, whereas central Geomarkets such as the City of Dallas, Dallas County, and Irving, Arlington, and Grand Prairie contributed a disproportionately larger share of Hispanic and Black prospects. These racial/ethnic disparities become significantly more pronounced, particularly in the disproportionate share of Asian prospects, as PSAT score thresholds increase (see Appendix **?@fig-dallas-rq2-lowSAT-race** and **?@fig-dallas-rq2-highSAT-race**). Similar Geomarket contribution patterns are also evident by first-generation college student status, with Collin and Rockwall Counties and the West of Dallas/Fort Worth Metroplex providing larger shares of non-first generation college student prospects, and central Geomarkets (City of Dallas, City of Fort Worth, Dallas County, and Irving, Arlington, and Grand Prairie) providing disproportionately larger shares of first-generation college student prospects. Moreover, central Geomarkets are particularly important for including Black (City of Dallas and City of Fort Worth), Hispanic (City of Dallas, City of Fort Worth, Dallas County, and Irving, Arlington, and Grand Prairie), and Asian (City of Fort Worth and Irving, Arlington, and Grand Prairie) first-generation college students.

While Collin and Rockwall Counties and the West of Dallas/Fort Worth Metroplex Geomarkets still contribute a notable overall number of Black, Hispanic, and Asian prospects, such students are predominantly not first-generation college students.

5.3 Los Angeles

Decentralized Diversity and Income in a Multi-Nucleo in the Los Angeles Geomarket Landscape

The 11 Geomarkets within the Los Angeles metropolitan area are illustrated in Figure 16 by total population across the three census periods. The Los Angeles metropolitan area is one of the only multi-nuclei models in the country that is formed when urban growth occurs around multiple centers that serve different functions rather than expanding from a single central business district core (CITE- Harris and Ullman 1945). As depicted in Figure 16, Geomarkets closely follow this overall metropolitan model. Hollywood and Wilshire, South and South Central Los Angeles, and East Los Angeles Geomarkets are centrally located in the metropolitan area followed by an outer core ring of made up by the Glendale and Pasadena, San Fernando Valley-East, West Los Angeles and West Beach, South Bay, and Long Beach Geomarkets. The San Fernando Valley-West Geomarket is located in the northwest part of the region, whereas Covina and West Covina as well as the Riverside, San Bernadino, and Ontario Geomarkets are located inland.

The population growth in the Los Angeles metropolitan area increased from approximately 8 Million in 1980 to more than 12 Million in 2020. Figure 9 showcases population growth by Geomarkets over the three census periods reflect the urban sprawl forming the multi-nuclei model. The most pronounced increases occurred in South and South Central Los Angeles Geomarket, as well as the outer/inland Geomarkets of San Fernando Valley-West, Riverside and San Bernadino, and Ontario. The South and South Central Los Angeles Geomarket grew from approximately 1.2 to 1.6 Million from 1980 to 2020. In contrast, the San Fernando Valley-West and Riverside and San Bernadino, and Ontario Geomarkets grew from approximately 700,000 to 1.2 Million and from 1.1 Million to nearly 3 Million during this time, respectively.

@fig-la-rq1-race presents the racial and ethnic composition of each Geomarket within the Los Angeles metropolitan area from 1980 to 2020. Over this period, the proportion of White residents declined across all Geomarkets, while Asian and Hispanic populations generally increased. In 1980, all Geomarkets - except for East Los Angeles, South and South Central Los Angeles, and Hollywood and Wilshire- were predominantly White, with percentages ranging from 62% White in Long Beach to 78% in the San Fernando Valleys (West and East) Geomarkets. By 2020, however, only the West Los Angeles and West Beach Geomarket remained predominantly White (62%). Remanining Geomarkets exhibited a more racially/ethnic diverse population by 2020, including San Fernando Valley-West- (44% White, 4% Black, 39% Hispanic; 11% Asian Pacific Islander), San Fernando Valley -East (43% White, 4% Black, 41% Hispanic; 8% Asian Pacific Islander), Glendale and Pasadena (35% White, 3% Black, 37% Hispanic; 21% Asian Pacific Islander), South Bay (29% White, 12% Black, 33% Hispanic; 21% Asian Pacific Islander), Long Beach (26% White, 11% Black, 46% Hispanic; 13% Asian Pacific Islander), Covina and West Covina (19% White, 3% Black, 52% Hispanic; 24% Asian Pacific Islander), and Riverside, San Bernardino, and Ontario (28% White, 7% Black, 54% Hispanic; 6% Asian Pacific Islander). However, the South and South Central Los Angeles and Hollywood and Wilshire Geomarkets experienced substantial declines in the share of Black residents from 1980 to 2020, dropping from 44% to 18% and 18% to 9%, respectively.

Figure 18 presents trends in socioeconomic indicators for the Los Angeles metropolitan area from 1980 to 2020. While median income increased across all of the metropolitan area over the three census periods, some shifts occurred in the relative socioeconomic levels across Geomarkets. Many Geomarkets kept their relative levels of affluence from 1980 to 2020. For instance, the Covina and West Covina, South Bay, and San Fernando Valley remained among the most affluent, whereas the San Fernando Valley East, Glendale and Pasadena, Long Beach, and Riverside, San Bernardino, and Ontario Geomarkets remained at middle ranges of affluence and the Hollywood and Wilshire, South and South Central Los Angeles, and East Los Angeles Geomarkets remained at the lowest levels of affluence across the metropolitan area during this period. The West Los Angeles and West Beach Geomarket demonstrated the most substantial increase in median household income, rising from $112,000 in 1980 to $132,000 in 2000, and reaching $137,000 by 2020. This sustained growth positioned it as the most affluent Geomarket in the Los Angeles metropolitan area.

Figure 18 also illustrates shifting levels of poverty across Geomarkets in the Los Angeles metropolitan area over time. In 1980, poverty rates were relatively low (less than 12%) for all Geomarkets except for East Los Angeles (17%), South and South Central Los Angeles (24%), and Hollywood and Wilshire (18%). However, poverty rates declined in South and South Central Los Angeles (22%), remained stable in East Los Angeles and Hollywood and Wilshire, and increased in all other Geomarkets. Such shifts and West of Dallas/Ft. Worth Metroplex, while increasing for all other Geomarkets. These divergent trends resulted in more staggered poverty rates across the metropolitan area by 2020. This includes four Geomarkets with poverty rates less than 10% (San Fernando Valley- West, West Los Angeles and West Beach, South Bay, and Covina and West Covina), four Geomarkets with poverty rates ranging from 11%-15% (San Fernando Valley- East, Glendale and Pasadena, Long Beach, and Riverside, San Bernardino, and Ontario), and three Geomarkets with poverty rates ranging from 16%-22% (Hollywood and Wilshire, East Los Angeles, South and South Central Los Angeles).

Lastly, Figure 18 shows a widening disparity in educational attainment across the Los Angeles metropolitan area. Although all Geomarkets experienced increases in the percentage of residents with a bachelor's degree or higher between 1980 and 2020, the West Los Angeles and West Beach Geomarket experienced a substantially greater increase - from 35% in 1980 to 66% in 2020- widening the gap with other Geomarkets in terms of educational attainment.

The Los Angeles metropolitan area exemplifies a complex multi-nuclei urban model, characterized by decentralized population growth and increasing demographic diversity across its 11 Geomarkets. From 1980 to 2020, the region's population expanded significantly leading to overall declines in the White population and increases in Hispanic and Asian populations across Geomarkets. West Los Angeles and West Beach is the only majority White Geomarket in 2020. Socioeconomic indicators reveal enduring disparities, especially in historically lower-income Geomarkets like South and South Central Los Angeles, East Los Angeles, and Hollywood and Wilshire. Meanwhile, Geomarkets such as West Los Angeles and West Beach became increasingly affluent and highly educated, highlighting growing socioeconomic and educational divides. Given these demographic shifts within the context of a multi-nuclei urban model, the Los Angeles metropolitan area presents a distinctive Geomarket landscape case in which racial/ethnic enclaves across a range of various socioeconomic levels are distributed across multiple Geomarkets rather than concentrated in one or two.

Composition of Students Lists by Geomarkets

To examine how the socioeconomic and racial composition of included versus excluded prospects varies when student list purchases filter on particular Geomarkets in the Los Angeles metropolitan areas, we analyze six orders placed by a research university filtered for prospects across the entire state of California, in the 2019-2020 high school graduating class, and by PSAT scores. Two orders indicated PSAT score thresholds ranging from 1070-1180, another two orders filtered for a 1190-1260 PSAT range, and the remaining two orders filtered for scores ranging from 1270-1520.

The racial/ethnic composition of purchased student profiles within Geomarkets in the Los Angeles metropolitan area is presented in Figure 19. The more than 15,000 prospects in the resulting student lists at the low PSAT score thresholds (1070-1180) reflect very similar racial/ethnic compositions within Geomarkets than overall demographic makeup of the metropolitan area in 2020 (see Figure 17). However, the racial/ethnic composition of prospects become less proportional to overall metropolitan patterns by Geomarket as PSAT scores increase. For instance, prospect pools at middle range PSAT scores (1190-1260) within Geomarkets become disproportionately more Asian, while the representation of Hispanic and Black prospects decline substantially. This pattern becomes most pronounced at the highest PSAT score prospect pools. This disproportionate over representation for Asian prospects in comparison to the population of residents with Geomarkets ranges from 3 percentage points in the West Los Angeles and West Beach Geomarket (16% prospects versus 13% Asian residents) to 52 percentage points in the East Los Angeles Geomarket (79% prospects versus 27% residents). Figure 19 illustrates the share of Black prospects within these high PSAT orders declines to less than 3% within all Geomarkets in comparison to Black residents making up a range of 3% (Covina and West Covina) to 18% (South and South Central Los Angeles) of residents within Geomarkets. Similar underrepresentation patterns are evident for Hispanic porspects are evident across all Geomarkets execept for a nearly equal representation in South and South Central Los Angeles (73% prospects versus 71% Hispanic residents).

Figure 20 presents the race/ethnicity of all prospects targeted in the middle PSAT score range across Geomarket contributions for the Los Angeles metropolitan area. For the more than 2,500 White prospects in this pool, we see the San Fernando Valley - West (28% versus 20% for all prospects) and the West Los Angeles and West Beach (12% versus 7% for all prospects)Geomarkets contributing disproportionately larger shares. Larger disparities across Geomarket contributions were evident for Asian, Black, and Hispanic students. The Glendale and Pasadena (17% versus 14% for all prospects), East Los Angeles (11% versus 5% for all prospects) and Covina and West Covina (17% versus 11% for all prospects) Geomarkets contributed a disproportionate larger share of Asian students, whereas nearly all other Geomarkets contributed disproportionately smaller or nearly equal shares.

Representational patterns across Geomarkets are reversed for Black and Hispanic prospects in Figure 20. South and South Central Los Angeles and Riverside, San Bernadino, and Ontario Geomarkets contributed larger proportions of Black and Hispanic prospects relative to their contributions to the overall prospect pool in the Los Angeles metropolitan area. On the other hand, the San Fernando Valley- West and the Glendale and Pasadena Geomarket contributed smaller proportions of Black and Hispanic Prospects. However, the West Los Angeles and West Beach (10% versus 7% for all prospects), Hollywood Wilshire (7% versus 5% for all prospects), and the Long Beach (8% versus 5% for all prospects) Geomarkets contributed a larger share of Black prospects, whereas Covina and West Covina contributed a larger share of Hispanic students. All other Geomarkets contributed nearly equal shares of Black and Hispanic prospects.

Contributions of each Geomarket to the pool of prospects from the Los Angeles metropolitan area based on first-generation college student status are presented in Figure 21. Only 889 of the more than 8,000 total prospects (11%) in this middle PSAT score range (1190-1260) pool were first-generation college students whose parents did not attend college. Only three of the 11 Geomarkets contributed substantially larger shares of these first-generation prospects: East Los Angeles (35%), South and South Central Los Angeles (47%), and Riverside, San Bernardino, and Ontario (15%). However, disproportionate contributions become more spread across Geomarkets for the nearly 1,436 of the more than 8,000 total prospects (18%) who were first-generation college students whose parents attended but did not complete their degree. Overall, six of the 11 Geomarkets contributed larger shares of these prospects: Hollywood & Wilshire (25%), East Los Angeles (26%), South and South Central Los Angeles (28%), Long Beach (25%), Covina and West Covina (22%), and Riverside, San Bernardino, and Ontario (22%). This leads to the remaining Geomarkets - San Fernando Valley- West (80%), San Fernando Valley- East (78%), Glendale and Pasadena (77%), West Los Angeles & West Beach (87%), South Bay (81%) - contributing disproportionately larger shares of not first-generation college students relative to the overall prospect pool (71%).

Lastly, Figure 22 presents Geomarket contributions to prospect pools by both first-generation college student status and race/ethnicity in the Los Angeles metropolitan area. Among all White prospects (n=2,511) whose contact information was purchased in this middle PSAT score range, approximately 3% were first-generation college students whose parents did not attend college, 11% were first-generation college students whose parents attended some college but did not complete their degree, and 86% were not first-generation college students. Figure 22 shows all Geomarkets contribute a nearly proportionate share of prospects by first-generation college students (across both no college and some college parents) relative to the overall pool. The South and South Central Los Angeles Geomarket stands out as one exception contributing a relatively larger share of White first-generation college students whose parents did not attend college (17%) and whose parent attended some college but did not complete their degree (33%). Other Geomarket that contributed signifcantly larger shares of White first-generation prospects whose parents did not complete their degree include Long Beach (17%), and Riverside, San Bernardino, and Ontario (19%).

Geomarkets contributions to first-generation college students was mixed across other racial/ethnic categories in Figure 22. For Asian prospects (11% first-generation no college, 21% first-generation some college, and 68% not first-generation), the Hollywood & Wilshire (12%) and East Los Angeles (36%) Geomarkets contributed larger proportions of first-generation college students whose parents did not attend college. The San Fernando Valley- East (28%), Hollywood & Wilshire (35%), East Los Angeles (25%), South and South Central Los Angeles (44%), Long Beach (27%), and Covina and West Covina (25%) Geomarkets also contributed larger proportions of first-generation college students whose parents attended college but did not complete their their degree.

For Black prospects (5% first-generation no college, 20% first-generation some college, and 74% not first-generation), Geomarkets that disproportionately larger proportions of first-generation college students whose parents did not attend college include South Bay (11%), South and South Central Los Angeles (21%), Long Beach (7%), and Covina and West Covina (9%). The West Los Angeles and West Beach (26%), Hollywood & Wilshire (36%), East Los Angeles (33%), Long Beach (40%), and Covina and West Covina (27%) Geomarkets also contributed larger proportions of Black first-generation college students whose parents attended college but did not complete their their degree.

Finally, Hispanic prospects in this middle range PSAT order were on average 25% first-generation college students whose parents did not attend college, 25% first-generation college students whose parents attended some college but did not complete their degrees, and 50% were not first-generation college students. The Hollywood & Wilshire (30%), East Los Angeles (39%), South and South Central Los Angeles (54%), and Riverside, San Bernardino, and Ontario (31%) contributed disproportionate shares of Hispanic first-generation college students whose parents did not attend college. The East Los Angeles (33%), South and South Central Los Angeles (28%), Long Beach (30%), and Riverside, San Bernardino, and Ontario (27%) also contributed larger Hispanic first-generation college students whose parents attended college but did not complete their their degree.

Despite Los Angeles's multi-nuclei urban structure contributing to a more decentralized Geomarket landscape with racial/ethnic diversity across a range of socioeconomic levels more spatially distributed across the metropolitan area, Geomarkets contributions to student prospect pools reflect racial and socioeconomic stratification patterns similar to other metropolitan cases in the study. Affluent Geomarkets like San Fernando Valley–West and West Los Angeles contribute an overrepresentation of White, Asian, and not-first generation college student prospects, the magnitude of which increases substantially as score ranges increase (see Appendix **?@fig-la-rq2-lowSAT-race** and **?@fig-la-rq2-highSAT-race**). On the other hand, more diverse and historically low-income Geomarkets, like South and South Central Los Angeles and Riverside, San Bernardino, and Ontario, contribute disproportionately more Black, Hispanic, and first-generation college student prospects. Similar to Chicago and Dallas-Fort Worth, Los Angeles further solidifies the pattern of some of the lowest-income Geomarkets consistently playing crucial roles in fostering college access for first-generation Asian (East Los Angeles), Black (South and South Central Los Angeles), and Hispanic college students (South and South Central Los Angeles, East Los Angeles, Hollywood and Wilshire, and Riverside, San Berdardino, and Ontario).

6 Discussion

The discussion of homophily by Chun (2021) describe the logic of The Market Segment model but also an underlying institutional logic of the enrollment management industry. The logic of homophily argues that there is a natural cultural match between students, that colleges should find students who look like students who enrolled at their institution in the past, and that colleges should recruit from the same schools and communities that are popular with peer colleges. We suggest that homophily is the operating logic most consistent with college recruiting behavior observed in the wild. For example, Jaquette et al. (2024) find great overlap in the sets of private schools visited by the University of South Carolina and the University of Alabama. The also find great overlap in the schools visited by Villanova and Notre Dame, with a disproportionate focus on visits to Catholic schools. When we observe that students at selective private colleges tend to be rich and that out-of-state students at public research universities tend to be rich (Chetty et al., 2020), this is partly because these universities devote most of their recruiting expenditures towards students from affluent schools and communities (Jaquette et al., 2024; Salazar et al., 2021). As Chun (2021) argues, observed homophily is not the result of voluntary action; rather, homophily is programmed into algorithms that create connections.

The Market Segment Model begins with the status attainment model, that student demand for college is a function of parental education and parental income. Zemsky & Oedel (1983, Chapter 3) demonstrated this argument by showing the correlation between student SAT score-sending behavior and measures of class. The thesis of the Market Segment Model is that that households of particular class and college aspirations are likely to live in particular parts of a metropolitan area and that these geographic territories can be meaningfully captured by Geomarkets. Although Geomarkets appear coarse by contemporary standards, they were a landmark innovation in Geographic segmentation. The Market Segment Model recommends that colleges should identify their core student market segment – local, in-state, regional, or national – identify Geomarkets that contain large numbers of households from this market segment, and then target high schools and communities within these Geomarkets. This information is contained in the Market Segment Profile (Appendix A), a standard ouput in EPS software. When considering new Geomarkets to target, colleges should utilize the logic of homophily by identifying Geomarkets that are popular with peer colleges. This information is contained in the Institutional Profile (Appendix A), also included in EPS software.

Zemsky & Oedel (1983) state that the Market Segment Model merely formalizes the operating logic of college admissions officers. For admissions officers at selective colleges, the logic is that good students from good families are willing to attend good colleges that are far from home. These good families are found in particular parts – Geomarkets – of metropolitan areas. By contrast, students from other parts of the metro possess the disposition and achievement to attend their local college. The Market Segment Model formalized this logic and commodified it in EPS software that helped colleges identify desirable Geomarkets and desirable high schools within those Geomarkets. Espeland & Stephens (2008) suggest that, once commodified and quantified, the local knowledge of admissions officers becomes redundant.

Research question 1 investigates racial and socioeconomic variation between and within Geomarkets over time. We find that Geomarkets are highly correlated with race and class. [KARINA SUMMARIZE FINDINGS IN A COUPLE SENTENCES; REVISE PARAGRAPH AS NECESSARY] We show that in 1980, when Geomarkets were being created, that Black people tended to be highly concentrated in the poorest Geomarket in the metropolitan area. Examples include, CA7 – City of Oakland, MA 6 – Boston & Cambridge, OH 4 – City of Cleveland (East), TX17 – City of Houston (East), TX19 – City of Dallas, CA21 – South & South Central Los Angeles, and PA5 – Philadelphia County. In a handful of metropolitan areas (e.g., Cleveland), Black people remain conentrated in the poorest Geomarkets. In Chicago-Land, [KARINA – ONE OR TWO SENTENCES]

These findings are not surprising given the extent of race and class segregation in the US. Furthermore, the correlation between Geomarkets and class is expcted because Geomarket borders were created in service of conceptual model that views demand for higher education as a function of class. Zemsky & Oedel (1983) is written around New England, with a particular focus on Geomarkets in Connecticut and Massachusetts. Zemsky & Oedel (1983) do not discuss the intersection of student demand and race. Although unsurprising for early 1980s social science, this silence is conspicuous considering the salience of political controversy surrounding "busing" in Boston and nearby metropolitan areas.

Research question 2 analyzes the racial and socioeconomic composition of student list purchases. We examine purchases that include all Geomarkets around a metropolitan area in order to assess the potential consequences if including/excluding particular Geomarkets from the purchase. This question is motivated by the Zemsky & Oedel (1983) recommendation that selective colleges that enroll students from the regional and national market segment should target affluent Geomarkets, while community colleges and non-selective 4-year colleges should focus on middle- and working-class Geomarkets. KARINA – ADD TEXT SUMMARIZING RESULTS.

This article adds a new perspective to existing explanations about how students are sorted into colleges. The status attainment model argues that college destination is a function of parental education and occupation (Sewell & Shah, 1967, 1968b, 1968a). The Market Segment Model is the status attainment model applied to geodemographic market research [CITE]. Fishman (2020) finds that the educational achievement of Asian American students whose parents are immigrants tend to have high educational achievement even if their parents do not, while the educational achievement of later-generation Asian Americans conforms to status attainment theory. In our analyses of prospects included in student list purchases, Asian American prospects from poor Geomarkets tended to be first-generation students while Asian American prospects from affluent Geomarkets tended to have parents with a BA. Drawing from Fishman (2020), one explanation for this finding is that Asian students living in low-income Geomarkets tend to have parents who immigrated to the U.S. whereas Asian students living in affluent Geomarkets are more likely to have parents who were born in the U.S.

The cultural capital model explains a process by which upper and upper-middle class families sort themselves into selective colleges by providing their children with the pedigree (academic, extracurricular) valued by selective colleges, information about how to navigate the admissions gauntlet, and social networks that provide an inside track (Bourdieu, 1984, 1988; Huang, 2023; McDonough, 1997). This model explains how affluent households maintain a disproportionate enrollment share at selective institutions in an era of holistic admissions ostensibly designed to increase racial and class diversity (Huang, 2023). Both the status attainment model and the cultural capital model are demand-side explanations for why education is a “social sieve” (Jencks & Riesman, 1968; Stevens et al., 2008) that allows for a modicum of mobility while maintaining a much larger flow of intergenerational class transmission (Labaree, 1997). Chetty et al. (2020) – who obtained parental income from federal income tax returns for every U.S. college – show that the disproportionate enrollment share of high income families at selective private colleges – and even at most public research universities – is staggering. These patterns are consistent with the observation by Weber (1948, pp. 241–242) that educational credentials are property that "support their holders'…claims to monopolize socially and economically advantageous positions."

Supply-side explanations of credentialism and more recent scholarship on enrollment management complement the cultural capital model of sorting students to colleges. The credentialism literature recognizes that colleges have a financial incentive for educational credentials to determine the competition for socially and economically advantageous positions (Brint & Karabel, 1989; Collins, 1979; Labaree, 1997; Larson, 1977) and this credentials arms race favors affluent households. Scholarship on enrollment management describes which students colleges want to enroll and what colleges do to attract these students at different stages of the enrollment funnel (Cottom, 2017; Holland, 2019; Karabel, 1984, 2005; Khan, 2011; Killgore, 2009; Salazar et al., 2021; Stevens, 2007). Stevens (2007) and Khan (2010) describe a tacit arrangement between high school guidance counselors on the demand side and college admissions officers on the supply side. Counselors at well-resourced schools, especially private schools, are motivated to give their students a competitive advantage in admissions. Meanwhile, college admissions officers are motivated to enroll students who can afford full tuition price and are likely to donate in the future. These mutually beneficial desires are consummated by recognzing that upper and upper-middle class applicants satisfy the extracurricular needs of the college. The orchestra needs oboists. The lacrosse team needs players. Quantitative analyses of visits from colleges to high schools are consistent with Stevens (2007); selective private colleges and public research universities devote most of their recruiting resources on courting students from privileged schools and communities (Jaquette et al., 2024; Salazar et al., 2021). However, these analyses conceive of recruiting as something that is done by individual colleges.

Existing explanations of how students are sorted into colleges miss an important supply-side mechanism, third-party vendors that sort students on behalf of colleges. Zemsky & Oedel (1983) created the Market Segment Model and Geomarkets based on a snapshot of student demand from 1980. Zemsky & Oedel (1983) argues that demand for higher education is correlated with class, ignoring the historical structural barriers that produced class- and race-based inequality in 1980 student demand. In itself, the Market Segment Model is an unremarkable social science depiction. However, the College Board incscribed Geomarkets and the Market Segment Model into EPS software that told colleges which Geomarkets and high schools to target. Technologies that target target customers based on geography inevitably leverage racial and class segregation (Benjamin, 2019; Chun, 2021; O'Neil, 2016). Furthermore, technologies that use the logic of predictive analytics – identify correlates in past cases to make predictions for future cases – are prone to "pernicious feedback loops" (O'Neil, 2016). The structural barriers (e.g., segregation, slavery, Jim Crow) that caused historic place-based inequality in student demand are amplified because EPS recommends that colleges focus recruiting resources on localities that already have high student demand for peer colleges. Geomarkets were subsequently incorporated into the Student Search Service product. We show that that excluding low-income, non-white Geomarkets from student list purchases results in the disproportionate exclusion of first-generation, non-white students with strong test scores.

6.1 Enrollment Management Industry

The growing salience of third-party vendors warrants a reconfiguration of the organizational field salient to college access. DiMaggio & Powell (1983) [p. 148] define organizational fields as, "those organizations that, in the aggregate, constitute a recognized area of institutional life: key suppliers, resource and product consumers, regulatory agencies, and other organizations that produce similar services or products" and that "the virtue of this unit of analysis is that it directs our attention…to the totality of relevant actors." Sociological literatures salient to college access devote substantive attention to schools, colleges, families, and communities.College access scholarship from economics often analyzes the effects of district/state/federal (e.g., Fuller et al., 2023) policies and the effects of information interventions (Hoxby & Turner, 2013). These lines of research do not consider the growing role of third-party vendors, which are increasingly owned by private equity interests and offer software-as-service platforms that perform core functions for schools and colleges.[19]

Jaquette et al. (2022) describes four key dynamics in the enrollment management (EM) industry, with a focus on the market for student list data. First, EM consulting firms are central to the cre-

[19]Huang (2023) describes the role of independent admissions consultants hired by families as third-party vendors that engage on the demand-side.

ation and implementation of recruiting campaigns (Marcus, 2024). The top two EM consultancies are Ruffalo Noel Levitz, which claims to serve 1,900 colleges annually (Ruffalo Noel Levitz, 2025), and EAB, which claims to serve 2,100 colleges (EAB, 2025). College reliance on EM consultancies is partially explained by the high level of burnout and employee turnover in the EM profession (Hoover, 2023). When we issued records requests to public universities about their student list purchases, at least 50% of universities indicated that they outsourced student list purchases to an EM consultancy. In many cases, the university was buying names each year but no university employee had knowledge about which vendors they were buying from or which search filters they were utilizing.

Second, technological advances creates new means of identifying and serving prospects. College Board began selling the contact information of test-takers in 1972 (Belkin, 2019). ACT followed suit and the two testing companies enjoyed a near duopoly for several decades. This business can be described as list-based lead generation based on the direct-mail model. "Free" college search engines (e.g., Cappex, Niche) yielded news sources of student list data. Another data source is college planning software purchased by high school districts and utilized by high school students and guidance counselors. The most widely-known product is Naviance, which claims to be used by more than used by more than 10 million K-12 students and by 40% ofUS high schools (PowerSchool, 2021). *Naviance* college planning software feeds into the *Intersect* recruiting platform, which allows colleges to target Naviance users while they are on the platform. *Intersect* is an example of behavioral-based targeting.

The third dynamic in the EM industry has been the growth of test-optional movement, which reduces both the number of paying test-takers and the coverage of student list products sold by College Board and ACT. ACT responded to uncertainty in their core testing business by attempting to become an edtech company [CITE], failing [], and being acquired by Nexus Capital in 2024 [CITE]. Over the last two decades, the testing companies developed new search filters that explicitly incorporated predictive analytics – for example College Board's Geodemographic Segment filters [CITE] and ACT's predicted probability of enrollment filter [CITE] – developed free college search engines, and entered the enrollment management consulting market more aggessively. College Board has weathered the test-optional movement thanks to robust revenues from the Advanced

Placement product, but the decline in PSAT/SAT/PreACT/ACT test-takers has undermined their oligopoly in the market for student list data.

The fourth dynamic is the transformation from owner-operated to private-equity owned firms and erosion of the distinction between consultancy and software vendor. The 1980s and 1990s was a period of market entry in EM, when college admissions professionals or professors decided to hang up a shingle (Marcus, 2024). The 2010s were a period of acquisitions and concentration. After regulatory scrutiny pushed private-equity interests out of for-profit college market (Eaton, 2022), private equity investors find value in acquiring firms that provided services to direct providers. Drawing from resource dependence theory, Jaquette et al. (2022) describe the proliferation of horizontal acquisitions to grow market share and vertical acquisitions designed to make customers more dependent on particular recruiting products.

EAB exemplifies the the trend towards private equity ownership and industry concentration. EAB is the preeminent EM consultancy, offering software-as-service products along the domains of recruitment, pricing and financial aid, student success, and advancement (EAB, 2025). The origins of EAB trace to Bill Royall, who founded Royall & Company in 1983 to provide direct marketing and fundraising for Republican political campaigns (Jump, 2020). Royall did not sign its first colege client for several years, but EM became the primary focus by 1995. Royall was acquired by the health tech firm Advisory Board Company for $850 million in 2015 and then by Vista Equity Partners for $1.5 billion in 2017, renaming it EAB (Hansen, 2017).

As an owner-operated consultancy, Royall was the market leader in purchasing student lists from student list vendors on behalf of clients. Under Vista, EAB entered the market for student list data by completing a series of acquisitions that targeted the "leads" and "inquiries" stages of the enrollment funnel. In 2019, EAB acquired YouVisit, a leading provider of virtual tours. YouVisit is an engine for "inquiries" in that taking a virtual tour shows interest in a college and leaves a trail of contact information for subsequent recruiting interventions. In 2020, EAB acquired Cappex, a leading free college search engine, which is an engine for leads in that students provide contact details and other information. In 2021, EAB and PowerSchool – the leading provider of K12 student information systems and a subsidiary of Vista – jointly acquired the EM consultancy/software vendor Hobsons. EAB acquired Hobson's student success software, Starfish, while PowerSchool acquired Hobson's Naviance product and its sister recruiting product Intersect. EAB paid PowerSchool to become the exlusive reseller of Intersect. Finally, in 2022, EAB acquired Concourse, the leading "direct admissions" platform. EAB combined these acquisitions into create Enroll360:

> We spent the last couple of years creating a connected recruitment ecosystem that allows enrollment leaders to keep pace with students pursuing increasingly digital journeys to college. This work led us to join forces with several leading companies: Cappex, Intersect, Wisr, and YouVisit...Individually, each solution can solve important challenges at various stages of the enrollment funnel...By bringing these capabilities together, our vision is to reinvent how enrollment leaders reach their goals (Koppenheffer, 2021)

Enroll360 exemplifies a new kind of student list product that leverages proprietary data to sell software. Historically, College Board and ACT sold prospect contact information at a price-per-prospect (e.g., $0.50). The goal was to generate revenue from the sale of names. By contrast, Enroll360 wraps several proprietary databases of names (e.g., Cappex, Intersect) into a software-as-service platform that recruits those prospects at different stages of the enrollment funnel. Here, the goal of lists is to create demand for software, which is more expensive than names. Colleges that are interested in recruiting these prospects must buy an Enroll360 subscription. Like College Board *Student Search Service* contemporary software-as-service recruiting products incorporate search filters that enable colleges to choose which prospects they recruit. For example, reporting Feathers (2022) shows how the Intersect recruiting platform allows colleges to send paid advertisements to Naviance users. Intersect customers (colleges) control which Naviance users will receive recruiting messages by filtering on filters such as "academic ability," intended majors, and wheather students used Naviance to "research competitor institutions" (Feathers, 2022). A procurement document from the University of Utah explains that the Intersect subscription is necessary to recruit the proprietary database of Naviance users: (Sole Source, 2022):

> The marketing services being purchased operates within the PowerSchool Naviance platform, which is a proprietary system, that no other company has access to. There is unique group of prospective students who are only in the PowerSchool Naviance platform. We have spoken with several vendors where we can reach out to prospective students. Each vendor has their own proprietary website or database where select

students can be reached.

An under-studied and under-regulated third-party EM industry has negative consequences for colleges and for students. Accross multiple student list products, we see a growing number of filters that recommend which prospects to target based on the beheavior of previous cohorts of students. The ACT/Encoura "Enrollment Predictor" filter enables colleges to filter prospects based on the predicted probability of enrollment, which is created based on analyzing the enrollment decisions of previous cohorts of students (Schmidt, 2019). College Board Geodemographic Segment filters categorizes each Census Tract into one of about two dozen clusters based on the college-going behavior of previous cohorts (College Board, 2011b) and is based on the Claritas/PRIZM market segmentation system that categorized zip codes into groups useful for merchants (McKelvey, 2022). An investor-facing Vista Equity Partners (2025) video promoting EAB's "Pipeline Analytics" product states, "we are using artificial intelligence and machine learning to help schools build list of students that may be more more likely to enroll and persist in their university." The product "identifies students that would be a good match for a school based on their similarity to students who have succeeded there before and then provides them [the students] information about those institutions so that they choose to apply and ultimately enroll." Each of these products are based on the underlying logic of correlations and homophily discussed by Chun (2021) and applied by Zemsky & Oedel (1983). These products identify correlations in a historic snapshot of students and apply those relationships to make recommendations about which prospects to target in the present. As such, all of these technologies amplify the effect of previous inequality in student demand, which is itself a consequence of structural inequality in educational opportunity.

Market dynamics in the EM industry raise policy concerns about tuition prices, student choice, and competition in the market for EM consultancies may also affect competition, prices, and student choice. To the extent that colleges must buy expensive software to recruit prospects contained in an associated database, this expenditure will ultimately be passed on to students in the form of higher prices or reduced expenditure on education. Unfettered horizontal and vertical acquisitions in the EM industry causes the EM industry to become more concentrated. Smaller consultancies that do not control veritial inputs may be unable to compete with companies that have acquired proprietary pools of prospects. Fewer EM consultancies means less competition and higher consulting fees, which will be passed on to consumers. Finally, the blurring of the lines between consultancy and student list vendor suggests that large consultancies will funnel prospects only to those colleges that are willing and able to pay for subscriptions, which raises policy concerns about student choice.

6.2 Developing a Knowledge Infrastructure

Regulation of the higher education industry should be informed by research that investigates the "totality of relevant actors" (DiMaggio & Powell, 1983, p. 148) in the organizational field. Unfortunatel, scholarship salient to education policy and regulation have ignored two, related economic transformations. First, third-party vendors offer software platforms that perform core tasks of organizations, including schools and colleges (Jaquette et al., 2022). Second, private firms comprise a growing share of economic activity (Davis, 2016; Kalemli-Özcan et al., 2024). Most firms in EM and the broader edtech sector are private. However, private firms face fewer disclosure requirements than publicly traded firms. The paucity of research about third-party vendors that structure college access is substantially due to difficulty obtaining data for empirical analyses. The research community must figure out how to systematically investigate the role of private firms and investors in education, so that we can hold private interests accountable for education policy goals.

Knowledge infrastructures are "systems of observation and measurement" (Hirschman, 2021, p. 743) that provide the foundation for scalable research. They collect, process, and distribute data in ways that "enable certain kinds of knowledge production while simultaneously channeling researchers away from questions not readily answerable within…that infrastructure" (Hirschman, 2021, p. 742). The knowledge infrastructure of education research largely consists of data about students, schools, and colleges. It has been shaped by the ascendance of economics (Elizabeth Popp Berman, 2022), which incorporates district, state, and federal administrative data to evaluate the effects of schools and policies on student outcomes (Fuller et al., 2023). The research community mobilized to investigate for-profit colleges because for-profit colleges and students were included in ongoing data collection (Eaton, 2022). By contrast, researchers ignored the growth of private, for-profit, third-party vendors (e.g., PowerSchool, Parchment) because these organizations are excluded from data collections known to education researchers.

We argue that sociologists and adjacent scholars should expand the domain of the education research knowledge infrastructure to include third-party vendors in enrollment management, and edtech more broadly. This is a difficult task. Student unit record data owned by district, state, and federal agencies is simultaneously granular – can evaluate a particular policy – and macro – can speak to broad trends in the education sector. By contrast, obtaining granular data about third-party products in education is difficult because these data are owned by private interests that do not want researchers to interrogate their products (Cottom, 2020; Pasquale, 2015). We see two broad avenues for research: case studies involving primary data collection – including this study – which tend to have a granular focus on particular products or vendors; and secondary data analysis, which may have a more macro focus.

Although case study research often relies on interview and ethnographic data, another approach to data collection is to issue records requests to public entities that contract with third-party entities. For example, Hamilton et al. (2024) analyze public university contracts with online program managers (OPMs). The present manuscript is an example of case study research. We issued public records requests to obtain tabular data about student list purchases. However, this process was labor intensive, requiring the pro bono efforts of several law firms. Public records requests seem better suited to obtaining contracts. Qualitative or computational text analysis of publicly available websites and social media provides another avenue for data collection. Here, data collection is efficient but data processing is often labor intensive. Like investigative reporting (Feathers, 2022), case study research can produce granular analyses of particular products (e.g., Intersect, Enroll360) that yield insight into the underlying mechanisms of how third-party vendors structure college access. However, data collected for case study research typically does not meet the knowledge infrastructure standard of repeated, ongoing data collection that can be the foundation for scalable research.

We see subscription databases about private markets as having the potential to create a knowledge infrastructure for scalable research on the role of private firms and private equity funders in education, and also their role in other domains of interest to sociology. A growing set of "market intelligence" data providers serve the information needs of the investment community by providing data on private firms and deals involving private firms. These databases tend to include three broad "types" of data: (1) *firm-level data* (e.g., location, employees, financials); (2) *acquisitions*, encompassing who acquired whom and resulting ownership structure); and (3) *investments*, which include amounts/valuations/stake percentages of private equity investments. Some providers provide all three types of data (e.g., *S&P Capital IQ*, *LSEG Workspace*). Other providers specialize. For example, *PitchBook* is a leading provider of data about investments in private companies by private equity firms, while *Orbis* is a leading provider of firm-level data for non-U.S. private firms. These databases are often utilized in journals of finance or management that consider private equity markets or patterns of acquisitions (e.g., Humphery-Jenner et al., 2017; Kalemli-Özcan et al., 2024). Interestingly, the database subscriptions operate similar to contemporary student list products; an interactive, user-facing platform is wrapped around several sources of proprietary data. University libraries provides full or partial access to some subscriptions, while others must be purchased.

Although scholars cannot share subscription data, they can share code to process and analyze these data. We recommend that scholars develop panel datasets examining change over time in the firms operating in particular industries and acquisitions and private equity investments in those industries. For example, empirical scholarship can examine change over time in concentration in the enrolment management industry and its transformation from an owner-operated to a largely private-equity owned industry. Subsequent analyses could investigate the portfolio of large owners, their ties to other industries – such as the direct-provider for-profit college market – and the vertical inputs/technologies they are investing in.

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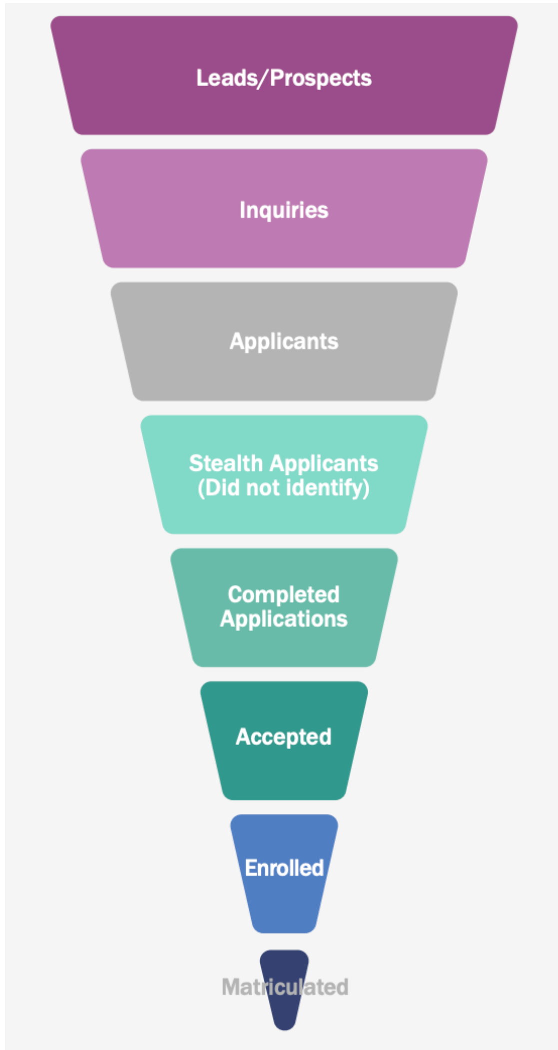

Figure 1: The Enrollment Funnel

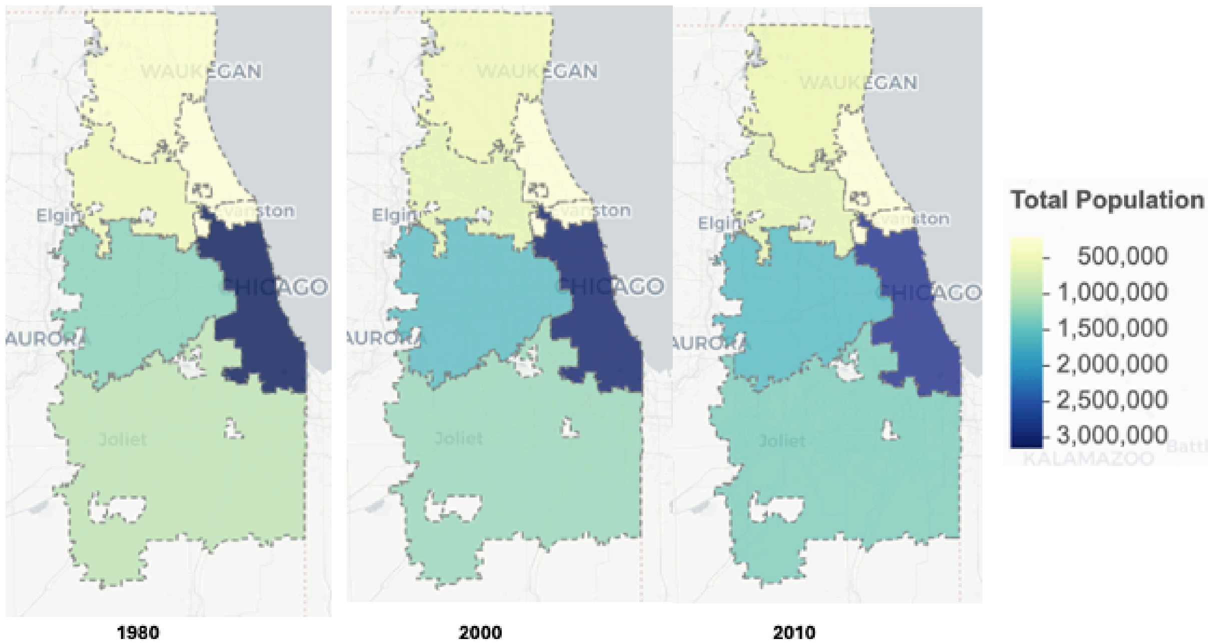

Figure 2: Chicago Geomarkets, Total Population 1980-2020

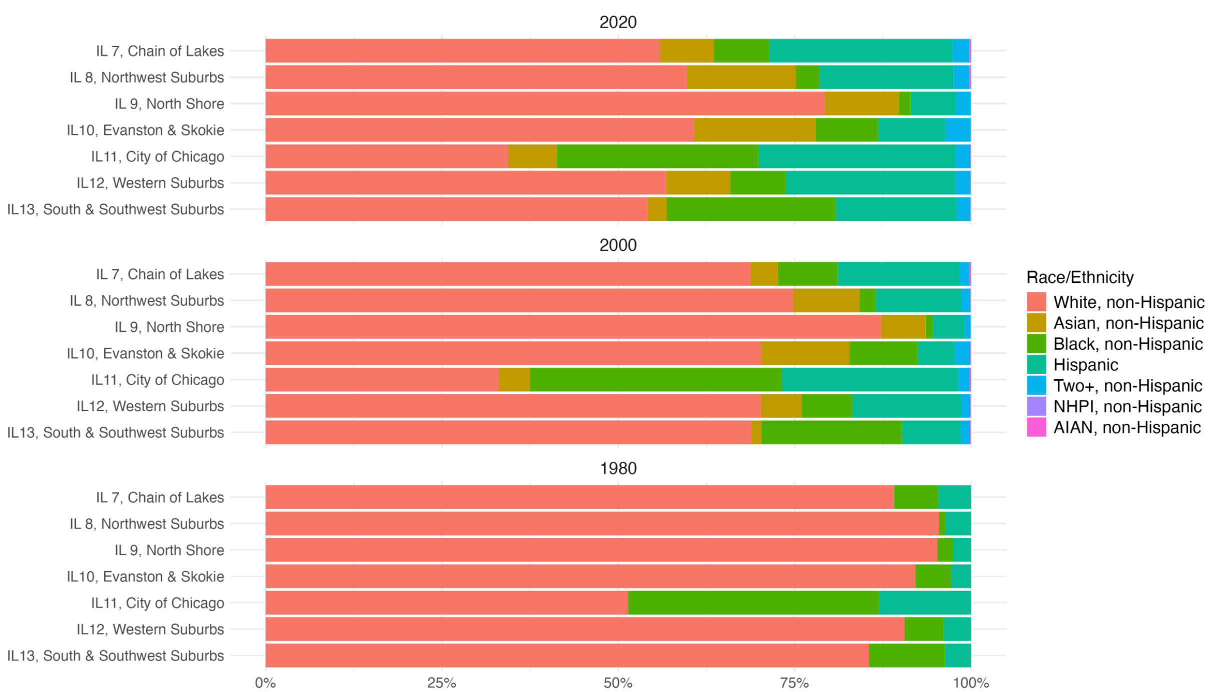

Figure 3: Racial/Ethnic Composition of Chicago Area Geomarkets, 1980-2020

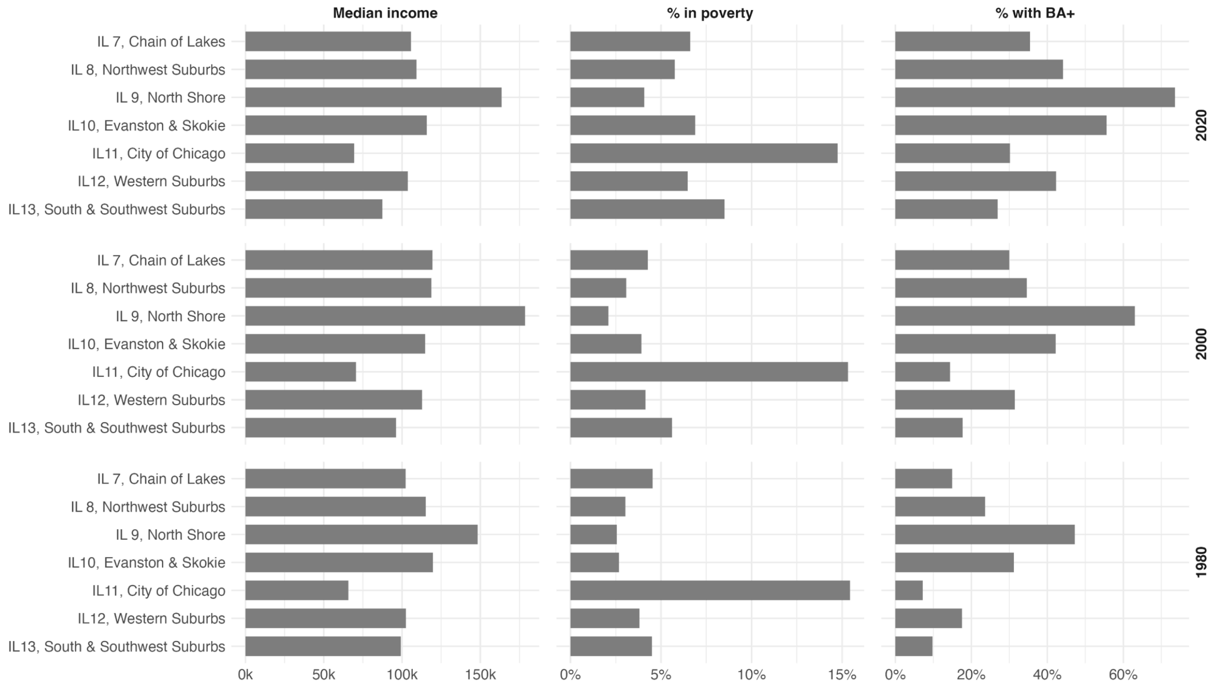

Figure 4: Socioeconomic Characteristics of Chicago Area Geomarkets, 1980-2020

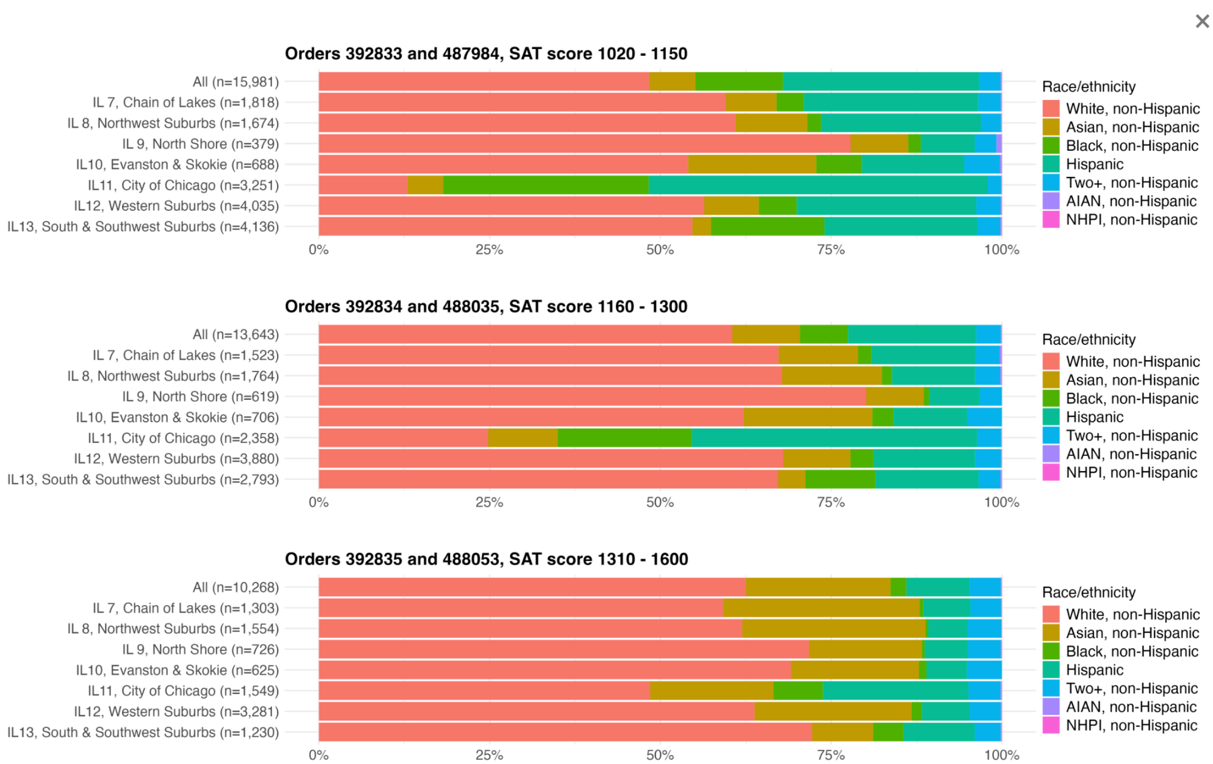

Figure 5: Racial/Ethnic Composition of Purchased Student Profiles by Geomarket, Chicago Area

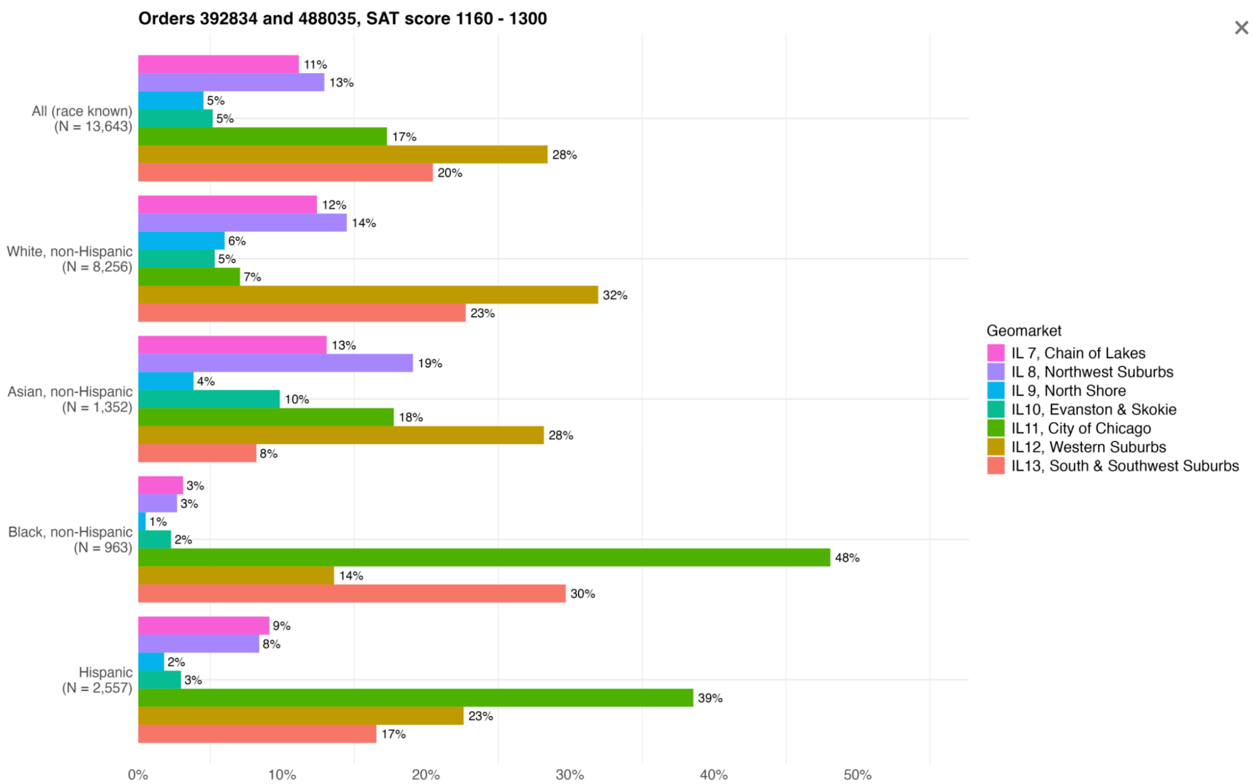

Figure 6: Chicago Geomarket Contribution to Purchased Student profiles by Racial/ethnic group, Middle-Range SAT orders

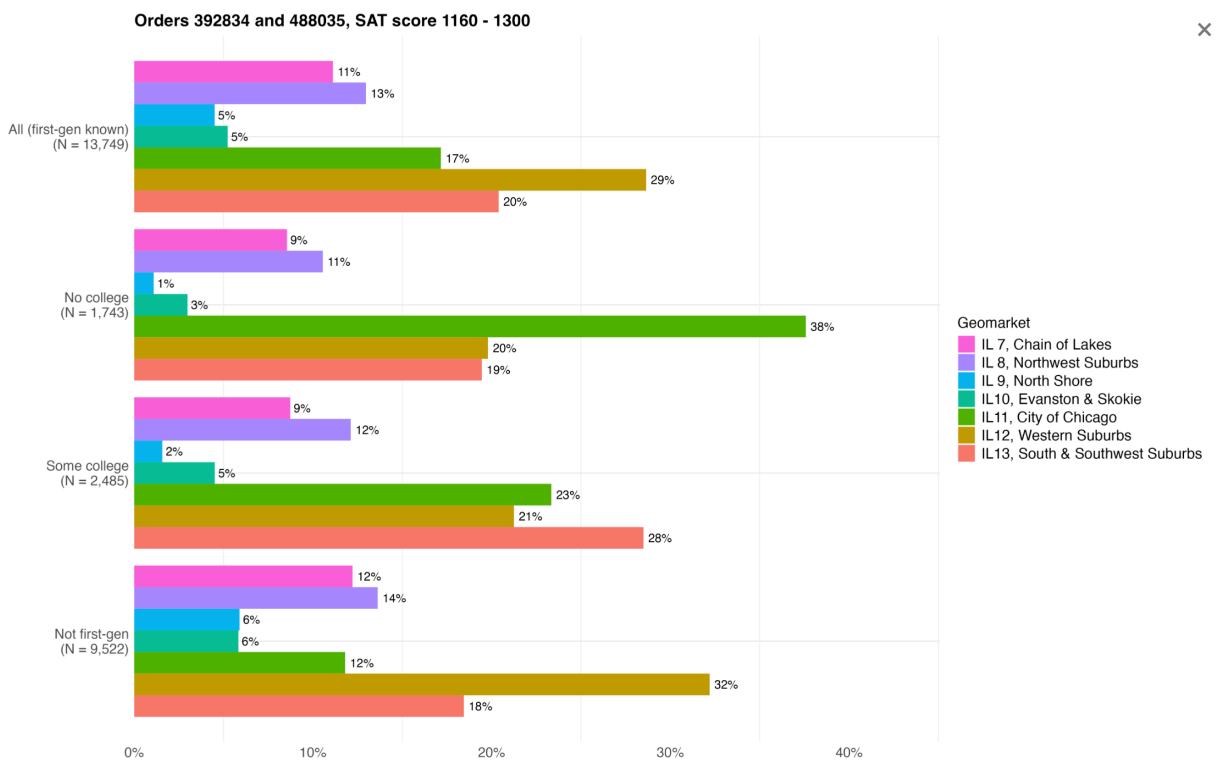

Figure 7: Chicago Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders

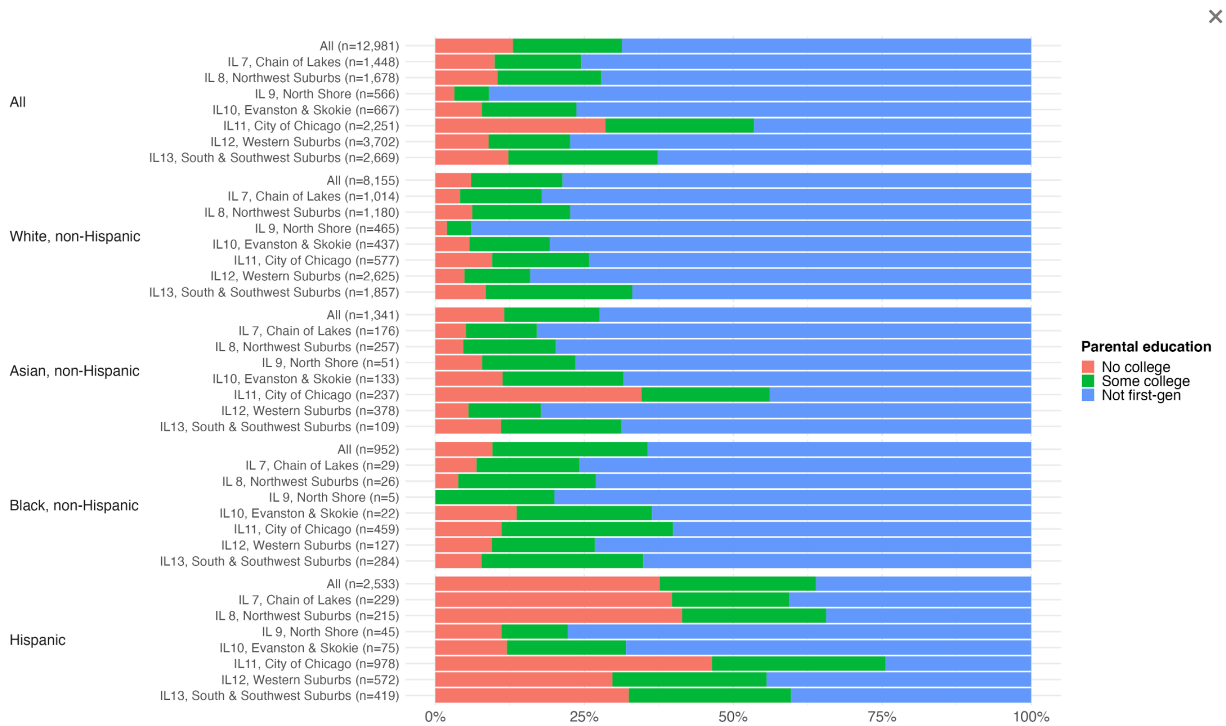

Figure 8: Chicago Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders

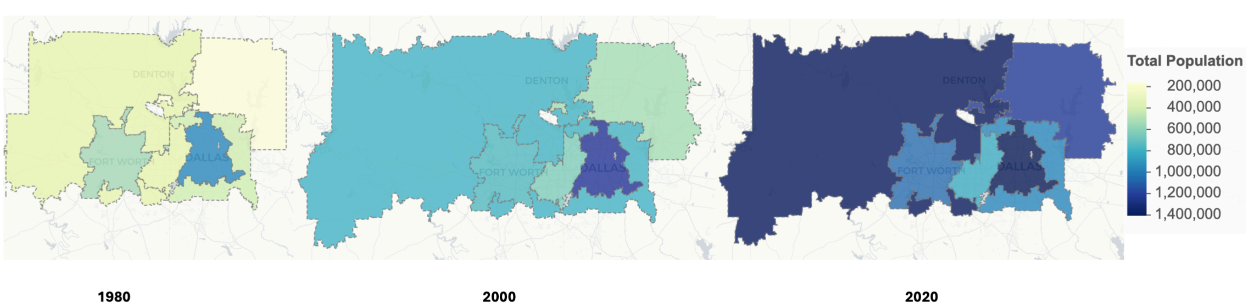

Figure 9: Dallas-Forth Worth Geomarkets, Total Population 1980-2020

Figure 10: Racial/Ethnic Composition of Dallas Area Geomarkets, 1980-2020

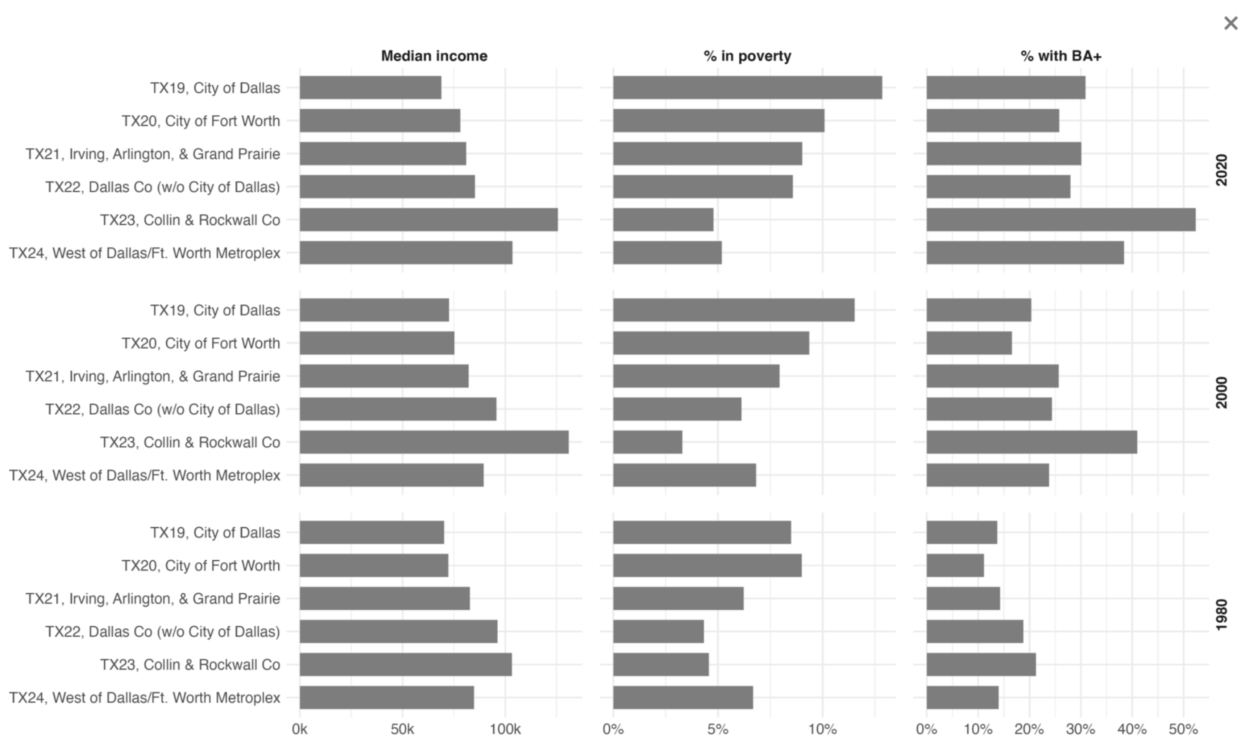

Figure 11: Socioeconomic Characteristics of Dallas Area Geomarkets, 1980-2020

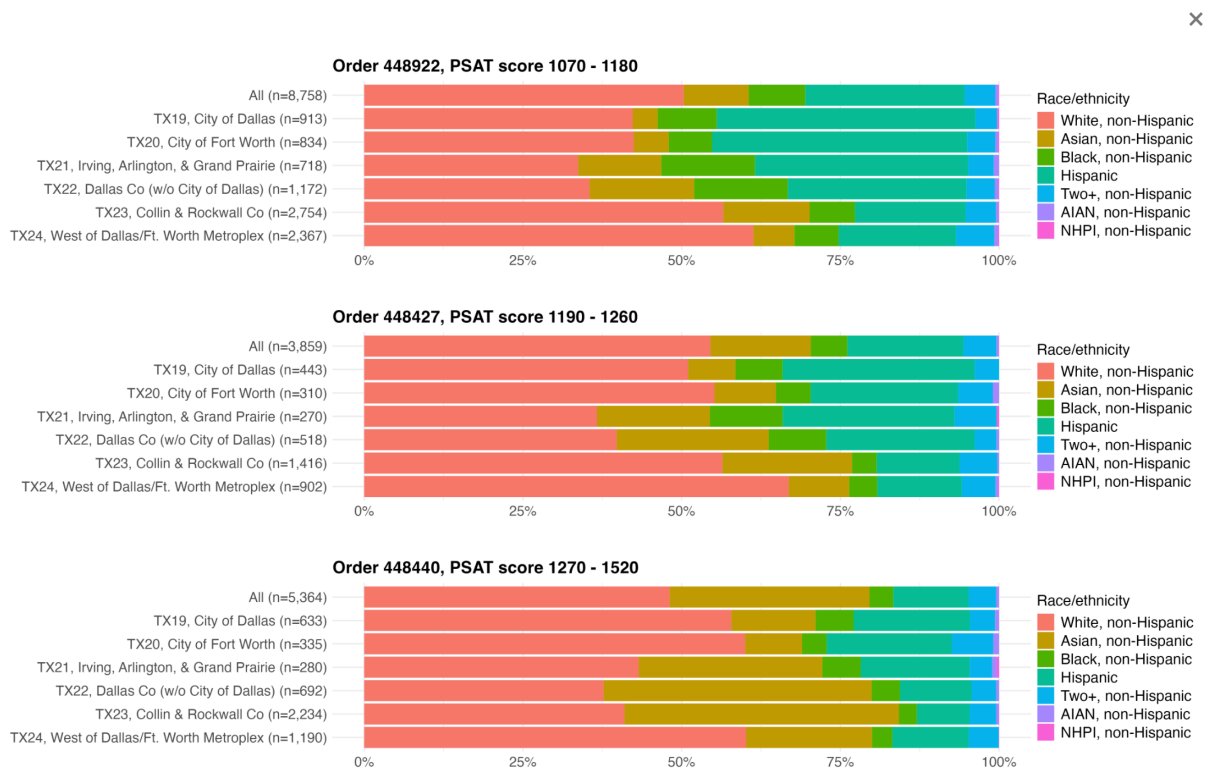

Figure 12: Racial/Ethnic Composition of Purchased Student Profiles by Geomarket, Dallas Area

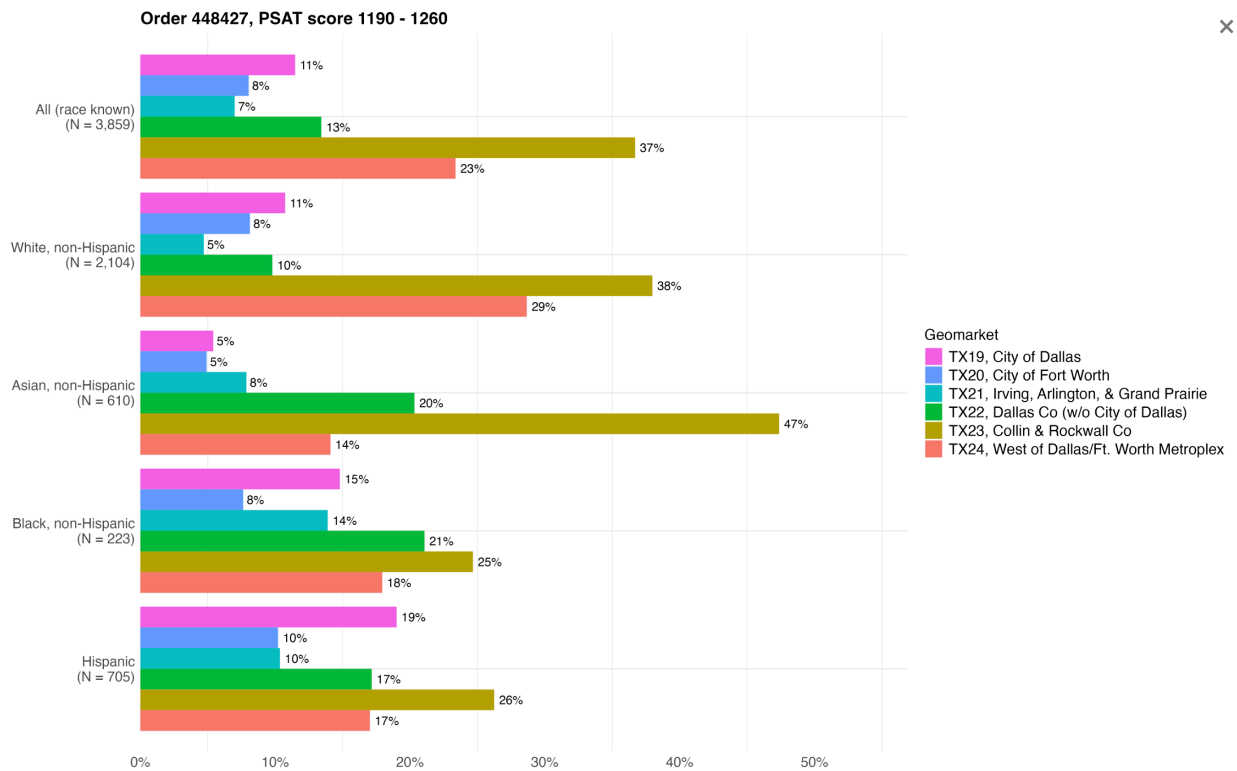

Figure 13: Dallas Geomarket Contribution to Purchased Student profiles by Racial/ethnic group, Middle-Range SAT orders

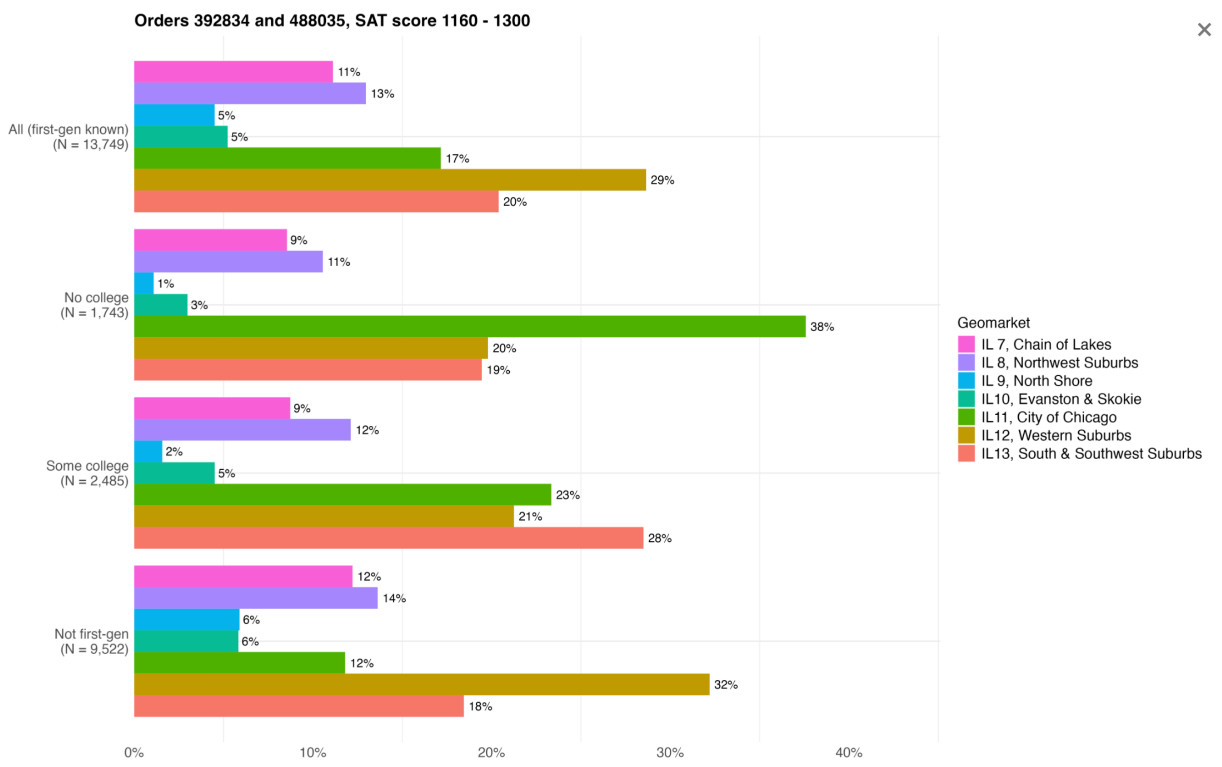

Figure 14: Dallas Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders

Figure 15: Dallas Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders

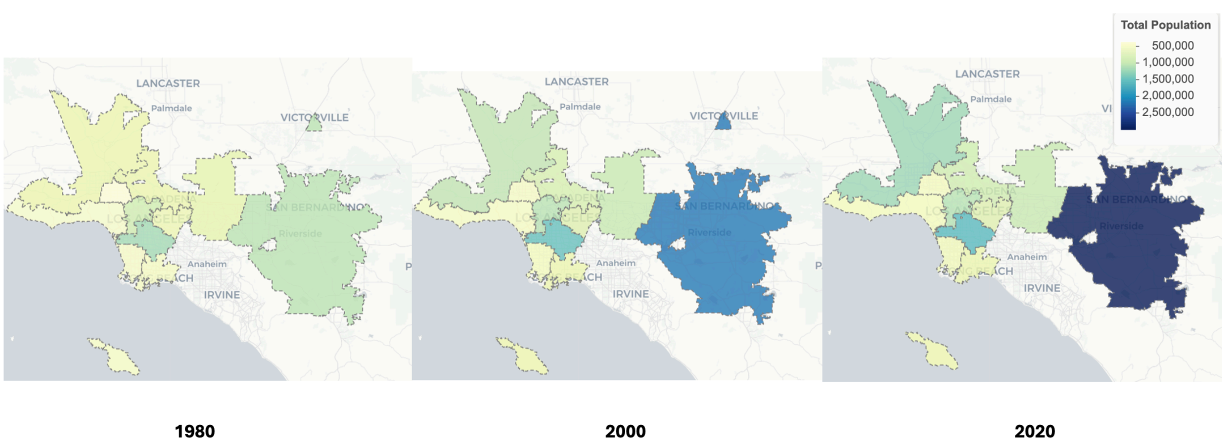

Figure 16: Los Angeles Worth Geomarkets, Total Population 1980-2020

Figure 17: Racial/Ethnic Composition of Los Angeles Area Geomarkets, 1980-2020

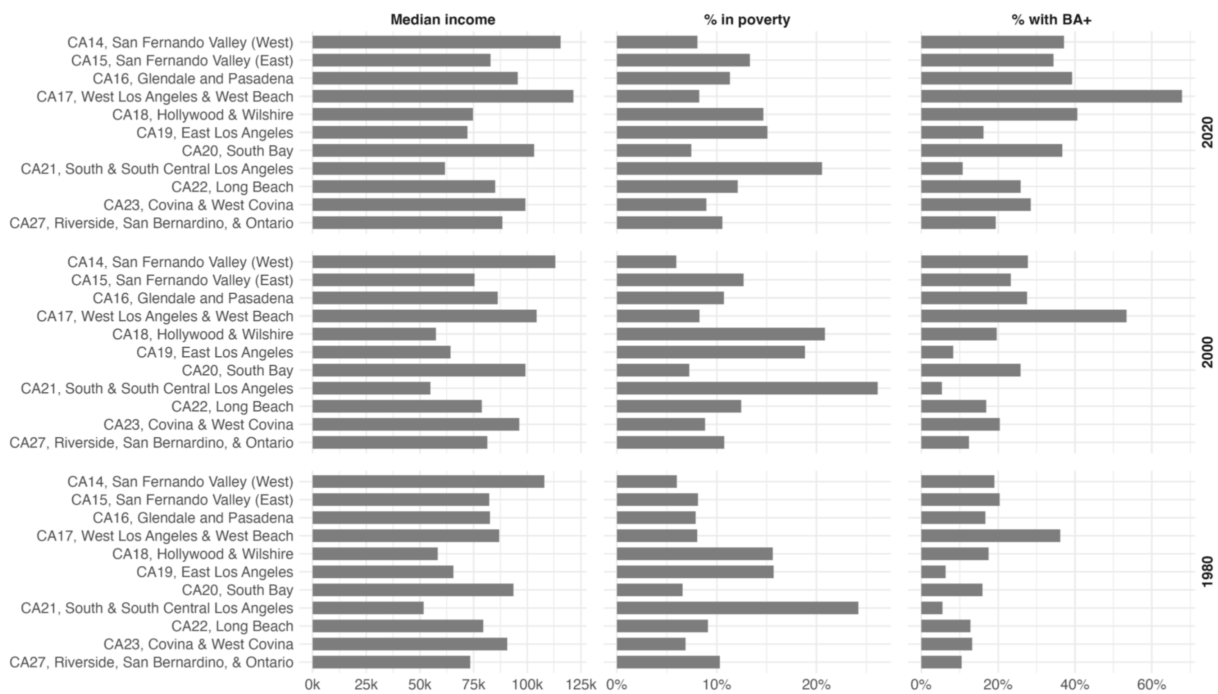

Figure 18: Socioeconomic Characteristics of Los Angeles Area Geomarkets, 1980-2020

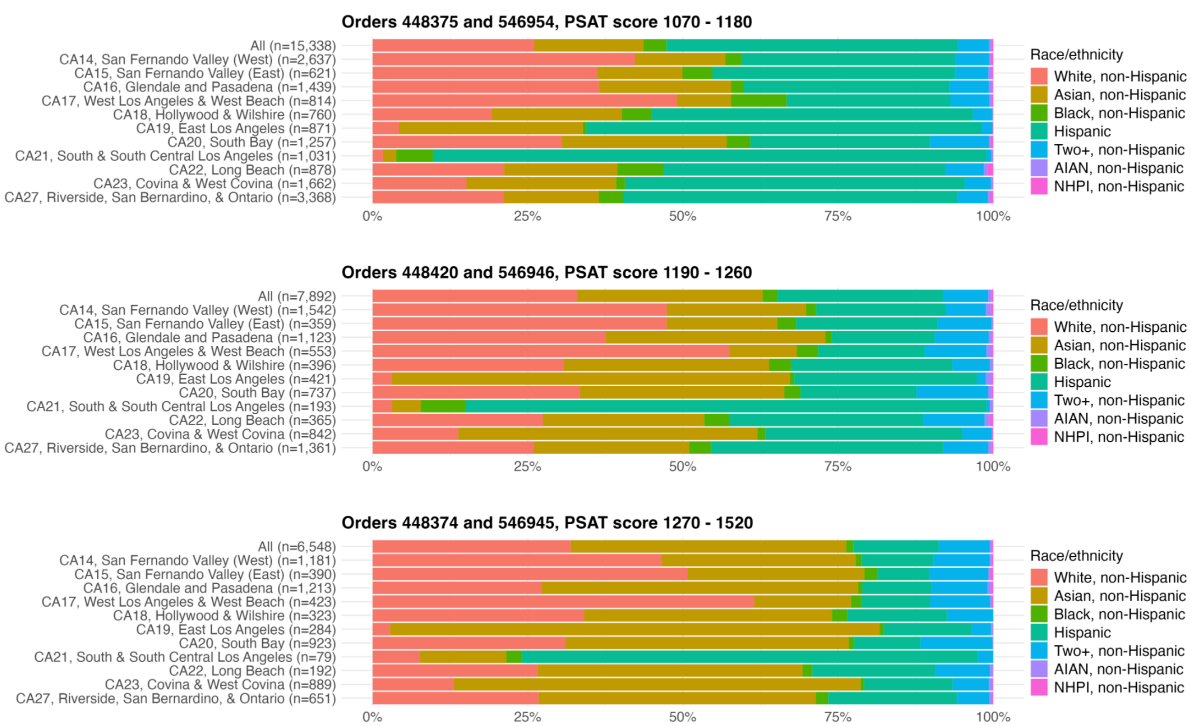

Figure 19: Racial/Ethnic Composition of Purchased Student Profiles by Geomarket, Los Angeles Area

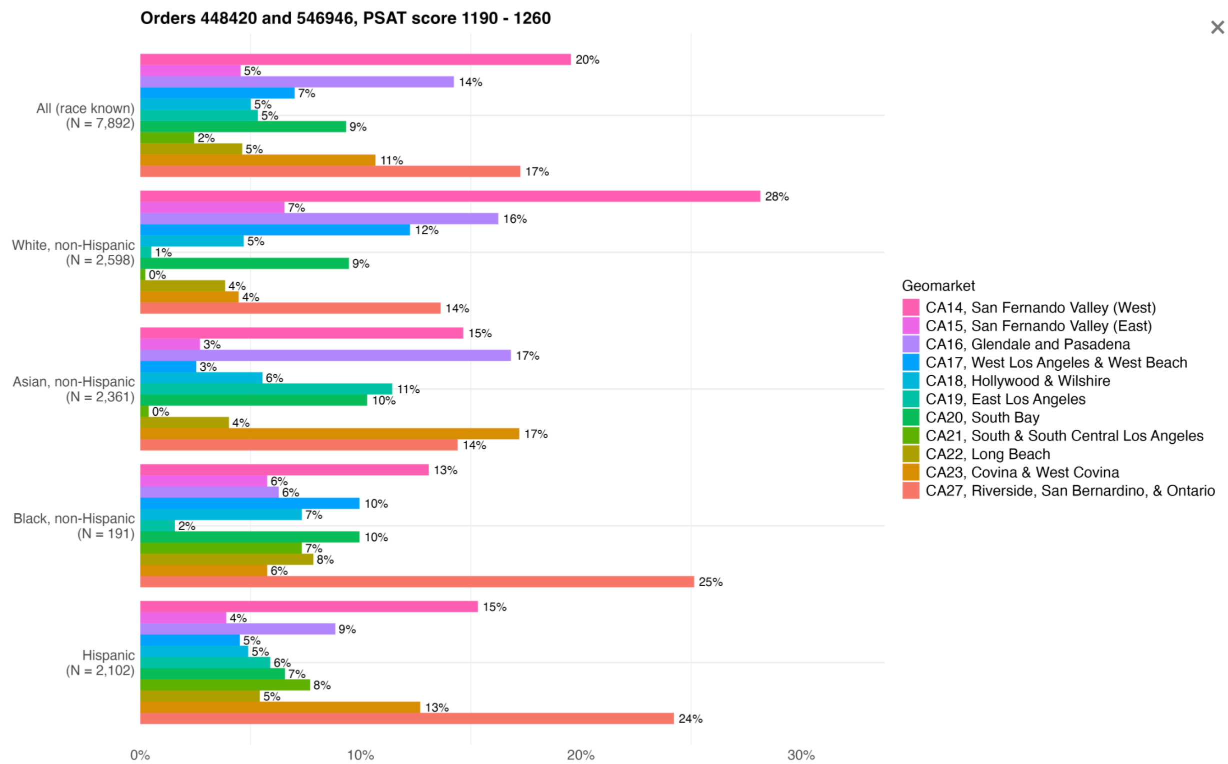

Figure 20: Los Angeles Geomarket Contribution to Purchased Student profiles by Racial/ethnic group, Middle-Range SAT orders

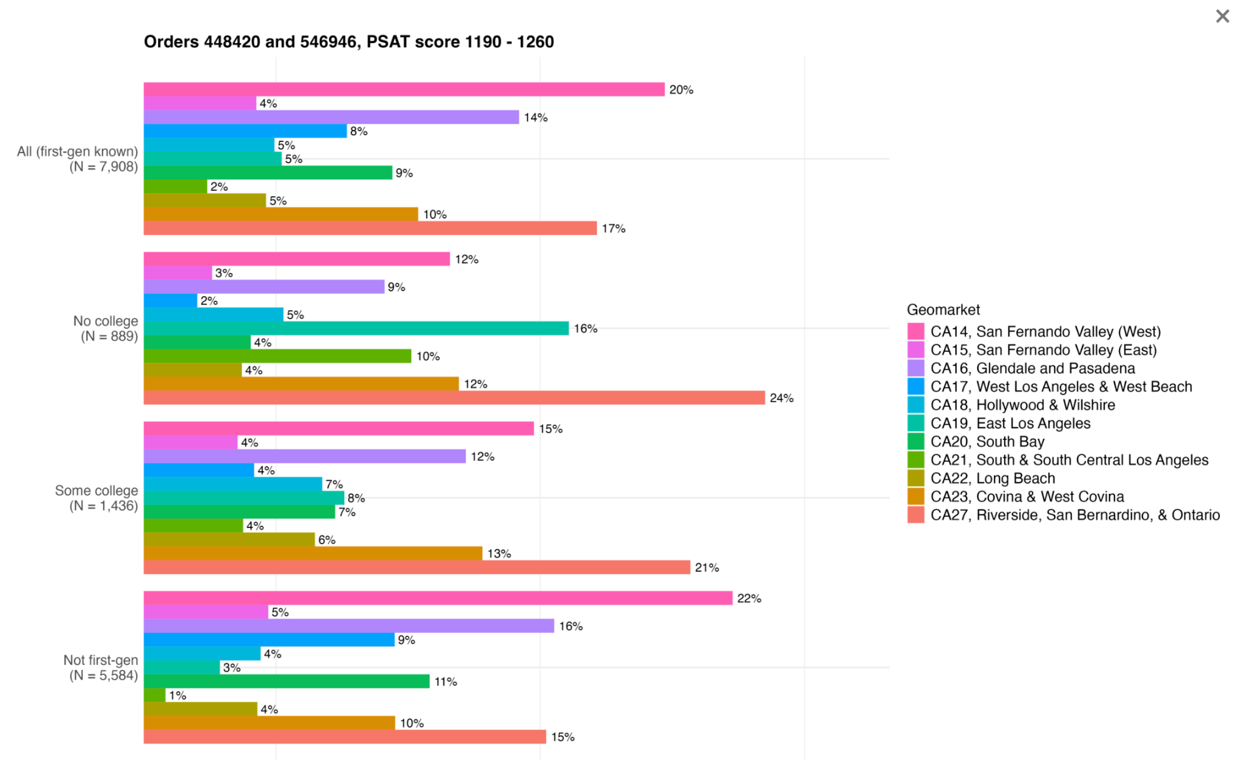

Figure 21: Los Angeles Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders

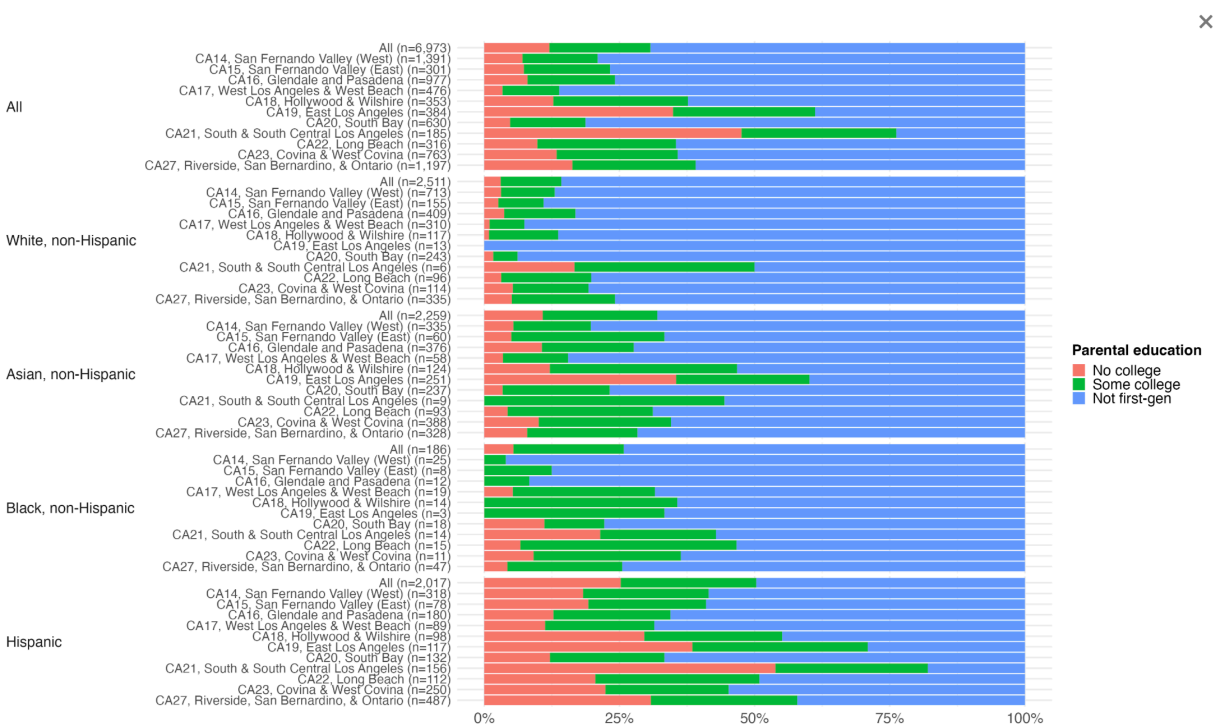

Figure 22: Los Angeles Geomarket Contribution to Purchased Student profiles by First-Generation Status, Middle-Range SAT orders