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

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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

In 1983, Robert Zemsky and Penney Oedel authored *The Structure of College Choice*. Based on an analysis of 1980 SAT score-sending behavior and published by *The College Board*, Zemsky & Oedel (1983) developed the Market Segment Model to help colleges recruit students. The underlying idea of the Market Segment Model is that student demand for your institution is fundamentally a function of class. Therefore, the key to recruitment is identifying territories where large numbers of your class live. Zemsky & Oedel (1983, p. 11) describe the Market Segment Model as an effort to "quantify" the knowledge that college admissions officers have about the geography of student demand:

Salazar, Jaquette, & Han (2022) say this:

> A good recruiter knows where to look for prospective applicants, as seen in the students' willingness or eluctance to travel. It is necessary to identify not only the most promising communities or poools, but also the specific neighborhoods within those communities – hence the recruiter's emphasis on feeder high schools. From the beginning, we have sought to mold our research to these concepts, to capture and quantify the phenomenon behind the folklore. Thus, it is the admissions officers' notion of admissions pools that dictates the geographic units of our analysis." [p. 11]

Zemsky & Oedel (1983) also created local "community based markets" (p. 14) – later known as "Geomarkets." Geomarkets are geographic borders that disaggregate states and large metropolitan areas for recruiting purposes. **?@fig-nyc-geomarkets** shows New York City area Geomarkets. In defining Geomarkets, Zemsky & Oedel (1983) did not draw new geographic borders, but rather made certain extant borders more salient to the process of recruiting.

Geomarkets have been incorporated into the supply-side structure of college access in ways that are simultaneusly mundane and fundamental. We posit three ways. First, Geomarkets became a principle for how many – if – admissions offices organized their labor. In states where a college recruits heavily from, admissions officers are often assigned specific Geomarkets as their territory [CITE]. Geomarkets were created to mirror the territories of admissions officers and, in turn, admissions offices structured their territories around Geomarkets. Second, The Market Segment Model and Geomarkets became the basis for Geomarkets are the basis for the College Board Enrollment Planning Service (EPS), founded in 1984 and still active today. EPS software recommends which Geomarkets a college should recruit from and which schools/communities they should prioritize within targeted Geomarkets. College Board (2010) says "Enrollment Planning Service (EPS®) the analysis tool that pinpoints the schools and geomarkets where your best prospects are most likely to be found." Noel-Levitz (1998) reports that, in 1995, 37% of 4-year public institutions and 49% of 4-year private institutions used EPS.

Third, Geomarkets were incorporated into the College Board "student list" product named Student Search Service. Student lists have been the primary source of lead generation in U.S. higher education since 1972, when College Board began selling "names" (Author, XXXX; Belkin, 2019). Ruffalo Noel-Levitz (2022b) reported that 87% of private and 86% of public four-year institutions purchase student lists. Lists contain contact information for prospective students. The Student Search Service database consists of College Board test-takers. Colleges pay a fee for each prospect (e.g., $0.50 in 2021). 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/exclude prospects from particular Geomarkets. An analysis of 830 student lists purchased by 14 public universities found that 16% of purchases filtered on Geomarket (Jaquette & Salazar, 2024).

Geomarkets have never been the subject of empirical research. This omission is surprising because the sociology of education is concerned with sorting (Domina, Penner, & Penner, 2017), particularly sorting into college. Traditionally, most scholarship – and certainly most scholarship in economics [HOXBY? CHETTY] – views inequality in college access as a function households or k-12 schools, which represent the demand-side of higher education. More recently, scholarship in the sociology of education takes seriously the idea that colleges are not passive recipients of applications, but rather they expend substantial resources soliciting demand from desirable applicants (Cottom, 2020; Holland, 2019; Stevens, 2007). However, most scholarship on recruiting analyzes the behavior of individual colleges (Salazar, 2022; e.g., Salazar, Jaquette, & Han, 2021), thereby creating the assumption that recruiting is a function of individual colleges. What these studies have missed is the broader enrollment management industry – third-party vendors, their products and consulting solutions – as a set of mechanisms that structure college access, funneling certain kinds of students to certain kinds of institutions.

This manuscript analyzes one of those mechanisms, The Market Segment Model and College Board Geomarkets, as a case study of quantification. We develop arguments from the broader literature on quantification (e.g., Espeland & Sauder, 2016; Espeland & Stephens, 2008; McArthur & Reeves, 2022), particularly the discussions of correlation and homophily from Chun (2021). Predictive analytics are based on correlation. When we use data on past correlations to make recommendations about the future, we amplify the effects of historic structural inequality. The Market Segment Model analyzes SAT score-sending data from 1980 and concludes that student demand for higher education is primarily a function of social class (Zemsky & Oedel, 1983). The Market Segment Model argues that homophily – actors that share characteristics are likely to form connections – is the organizing principle of student demand and competition between colleges. Zemsky & Oedel (1983, p. 72) state that "the hierarchical structure of collegiate competition largely reflects the stratified social and economic dimensions of the communities from which colleges draw their students." This snapshot of student demand in 1980, itself a consequence historic structural inequality, was programmed into the way admissions offices organize labor and programmed into the EPS and Student Service Service products that colleges utilize to identify and target prospective students. The result is a supply-side that reinforces structural inequalities observed on the demand-side.

[ADD TEXT SOMEWHERE AROUND HERE ABOUT WHY THIS TOPIC IS SIGNIFICANT AND IMPORTANT FOR CURRENT/FUTURE POLICY DEBATES: Why market segment model important. Software as service products dominate em industry and structure college access. Look at eab machine learning product But rarely do we see the recipe underneath these products. The book structuring college access is that recipe for EPS software]

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 the geomarket shapefile 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? We address this question by analyzing actual student list purchases that utilize commonly used search filters (e.g., PSAT score, GPA) but do not filter on Geomarkets. We simulate which prospects in particular metropolitan areas would have been included/excluded had the student list purchase filtered on particular Geomarkets. We obtained these data by issuing public records requests to public universities.

In the following section we provide background information about enrollment management and scholarship on recruiting. Second, we introduce core ideas and concepts from scholarship on quantification. Third, we apply these ideas to a close read of Zemsky & Oedel (1983) and motivate hypotheses. Four, we describe data and methods. Fifth, we present results. Finally, we discuss implications for scholarship and for policy.

A note from RESULTS that I texted to Bastedo on 12/19/2024

- But these geomarkets are pretty fucked up. They were designed to capture class. I see lots of orders that condition on test scores and rich geomarkets. But I know from similar purchases that don't condition on geomarket, that the high scoring first gen Asian and Hispanic students tend to come from the poor geomarkets that get excluded from a lot of purchases. By contrast, The Asian and Hispanic students that do get included in purchases that target rich geomarkets are usually not first gen

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, Ventresca, & Deng, 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, Sullivan, & Brodigan, 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, consisting of those that respond to an initial soliciation (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 (Author, XXXX). Purchased leads are served emails, brochures, and targeted social media advertisements 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, Berrey, & Rose-Greenland, 2016; Killgore, 2009; O. Y. A. Poon & Bastedo, 2022; Posselt, 2016; Taylor, Rosinger, & Ford, 2024). Economists often investigate financial aid leveraging, which seeks to convert admits to enrolled students [CITE].

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. Recruiting visits to high schools 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, Han, & Castañeda, 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 behaviors of individual colleges, scholarship on EM implicitly states that recruiting is something done by individual colleges. In addition to university personnel (e.g., admissions counselors, VP for enrollment management), the EM industry incorporates external stakeholders in the organizational field, 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 (Scott & Davis, 2007), enrollment management processes involve many "make or buy" decisions about whether to perform a given task in-house or outsource it to a third-party vendor (Author, XXXX). EM consulting firms 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 enrollment consulting firms – Ruffalo Noel Levitz and EAB – claim to serve more than 3,000 colleges and universities collectively (EAB, n.d.; Ruffalo Noel Levitz, 2023). 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 (Author, XXXX; Salazar et al., 2022).

Although the enrollment management industry is increasingly characterized by software-as-service products sold by private equity backed firms (e.g., for example, EAB's Enroll 360 product) (Author, XXXX), College Board products played a pivotal role in transforming recruiting from an in-house process to a process structured by third-party products. The Student Search Service, created in 1972, became the ubiquitous means of identifying prospects BLAH BLAH. Second, EPS, launcched 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 based on selected attributes while EPS encourages colleges to target Geomarkets and high schools based on the characteristics of households. THEREFORE WE REVIEW SCHOLARSHIP ON QUANTIFICATION.

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. 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) where students apply and enroll [CITE]. However, 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, applicants with 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 directors and admissions officers to make independent decisions about which applicants to admit, ideal class size, and curricular offerinags (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., O'Neil (2016); Noble (2018);]. 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 College Board 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 to assign levels of risk to each case. Chun (2021) provides the example of Kosinski, Stillwell, & Graepel (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.' "[1]

A bevy of 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 of time. The 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 whereby has been termed the "ratchet effect" (Harcourt, 2015) and "pernicious

[1] 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?'

feedback loops" (O'Neil, 2016).[2] 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. Chun (2021) argues that homophily is central to models that use correlation to predict future behavior. Homophily means that actors who share common characteristics are likely to form connections with one another, or "birds of a feather flock together." Homophily is a core assumption for network science (McPherson, Smith-Lovin, & Cook, 2001), in which actors – in this manuscript, high school students – are linked to one another through direct and indirect network ties – submitting SAT scores to the same college. Because network science models often draws from rational choice theory, they assume that homophily is the result of voluntary action by individuals, thereby "eras[ing] historical contingencies, institutional discrimination, and economic realities" (Chun, 2021, p. 95) that underlie behavior consistent with homophily. Chun (2021) problematizes the idea that homophily is a naturally occurring phenomenon. In commercial social networks (e.g., Faceboo, X, TikTok), homophily is more than an assumption; homophily is programmed into the algorithms that create connections between users.[3]

Within the market research profession, homophily is central to geodemography and the creation of market segments. 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

[2]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.

[3]Thus, Chun (2021, p. 82) writes, "echo chambers are not unfortunate errors, but deliberate goals" because "homophily is used to create agitated clusters of individuals whose angry similarity and overwhelming attrication to their common object of hatred both repel them from one another and glue them together."

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). M. 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 (Marion Fourcade & Healy, 2024).[4] Classification situations engender markets where a vertical hierarchy of products are targeted to a vertical hierarchy of consumers.

Reviewing scholarship on quantification, Berman & Hirschman (2018) argue that quantification has effects to the extent that stakeholders care about the numbers. U.S. law school rankings (Espeland & Sauder, 2016) and UK school league tables (McArthur & Reeves, 2022) exemplify this sort of salience. Studies of quantification in the sociology of education tend to study consumer-facing metrics. Law school rankings can be conceived as a business-to-consumer product because the goal is to inform consumers (prospective law school students) and consumers pay for the product. By contrast, market research helps businesses identify/target customers and can be conceived as a business-to-business (B2B) product because businesses pay for market research. To our knowledge, scholarship on quantification in education has not examined how third-party market research classifies consumers. Additionally, scholarship on college access has failed to analyze third-party products that colleges use to identify and target prospective students. This manuscript analyzes Market Segment Model (Zemsky & Oedel, 1983), which categorized high school students into vertical market segments 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.

Scholarship on quantification suggests the mechanisms by which market research reproduces structural inequality [CITE CHUN; SOME SOCIOLOGY]. Based on a snapshot of existing social stratification, market research matches verticially categorized consumers to vertically categorized pro-

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

ducers, thereby amplifying the effect of initial stratification on subsequent stratification. Unlike the analysis of UK school league tables, McArthur & Reeves (2022) we cannot show the effect of quantification. However, this study provides inisight about the mechanism underlying the effect. By analyzing and simulating *Student Search Service* purchases that filter on Geomarkets we show how Geomarkets reproduce historical race-based inequality in college access [THIS LAST BIT FEELS LIKE THE GENERAL CONTRIBUTION TO SOCIOLOGY].

3 The Market Segment Model and College Board Geomarkets

Creating the Market Segment Model. In 1978, Robert Zemsky, a University of Pennsylvania professor, was asked 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 researchers reached out to College Board because "we needed a database that described most institutions and most students…Coincidentally, the Board was reviewing its own efforts to help colleges estimate their enrollment potential, efforts which had faltered largely because the smallest demographic unit used in these analyses was the state' (Zemsky & Oedel, 1983, p. x). In 1979, College Board began providing data and funding for what became the *Comprehensive Undergraduate Enrollment Planning Project (CUEPP).* Zemsky & Oedel (1983, p. 4) write that,

> 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] state that "our initial task was to define enrollment markets in a manner consistent with admissions officers' intuitive understanding of student pools." Quoting an admissions officer, Zemsky & Oedel (1983, p. 11) write, " 'There are only three kinds of colege-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) created "three types of boundaries" (Zemsky & Oedel, 1983, p. 11), region, state, and community. The three regions were New England, Middle States, and the South. Next, "we 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."

These enrollment markets, later called "Geomarkets" by the College Board Enrollment Planning Service were intended to be consistent with the conception of a catchment market from the perspective of admissions counselors (Zemsky & Oedel, 1983). We know little about how geomarkets were created. Zemsky & Oedel (1983) write that,

> 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 these geographic boundaries, high school students were categorized into one of four different *market segments* – local, in-state, regional, and national – based on SAT score-sending behavior. Each institution a student sends SAT scores to can be defined as "local" (institution is in the same local market that the student lives in), "in-state" (same state but different local market), "regional" (same region but different state), or "national." In turn, a "local" student submits 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. The Market Segment Profile provides information about the number and characteristics of students in each market segment. This information is produced separately for each of the 143 Geomarkets. For example, Appendix Table A1 shows how many students in "CT3 – Fairfield County" are defined as regional or national based on their SAT score-sending behavior. 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. Appendix Table A3 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.

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 a simple software-as-service platform that informed college decisions about recruiting by essentially recreating the analyses of Zemsky & Oedel (1983). Institutions purchasing EPS could obtain the Market Segment Report for each local market and the Institutional Profile – their own and that of competitors – for each local market. Typical 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 (College Board, 2005).

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. Interestingly, the Geomarkets for New England, Middle States, and the South remain nearly identical to those developed by Zemsky & Oedel (1983). 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.[5]. Furthermore, this material encourages colleges to, first, identify which Geomarkets

[5]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

they will target. For example, 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.

Correlations. Chapter 3 of Zemsky & Oedel (1983) identifies the student characteristics associated 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. (Zemsky & Oedel, 1983) state that 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" (p. 33) and "The information derived from the Market Segment Model, however, is a remarkably ordered set of data, consistent in its relationships, that reflects the basic social and economic patterning associated with the structure of college choice" (pp. 34-35). [QUOTES REDUNDANT]

The primary takeaway of Chapter 3 is that student demand for higher education is mostly a function of social origin. For example, Zemsky & Oedel (1983) [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 "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."[6]

However, geomarkets differ in the relative abundance of students with particular socioeconomic characteristics and this has practical implications for recruiting. Zemsky & Oedel (1983) recom-

of individual states."

[6]The authors also find that these four variables predict student score-sending behavior at the Geomarket-level. Additionally, analyses reveal that the SAT score is the most important predictor of score-sending behavior, followed by parental education, family income, and educational aspirations. However, prior research shows that SAT scores are substantially a function of social origin (Sewell & Shah, 1967).

mend that colleges target Geomarkets with desirable compositions of socioeconomic characteristics and student market segment.

Homophily. Chapter 4 of Zemsky & Oedel (1983) – "The Company We Keep: Colleges and Their Competition" – shows that homophily is a core assumption of the Market Segment Model. The authors conduct a social network analysis that defines two institutions as being in competition with one another if at least 15% of students who sent SAT scores to one institution also sent scores to the other institution and vice-versa.[7] Zemsky & Oedel (1983, p. 42) sate, "we draw a fundamental conclusion about the structure of college choice: collegiate competition occurs principally between like institutions."[8] Subsequent analyses investigate the tuition price and 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. Zemsky & Oedel (1983, p. 72) describe these patterns as a natural process of homophily in which a vertical socioeconomic hierarchy of students is matched to a vertical hierarchy of universities:

> 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.

Research question 1 asks, what is the socioeconomic and racial variation between geomarkets in metropolitan areas and how does this variation change over time? 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. Additionally, Zemsky & Oedel (1983) created geomarkets in service of the Market Segment Model.

[7]We can think of students sending SAT scores to colleges as a "two-mode" social network in which students (mode 1) send SAT scores – the network tie – to colleges (mode 2). 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.

[8]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."

The Market Segment Model argues that socioeconomic status drives whether students belong to the local, in-state, regional, or national market segment. In turn, geomarkets are described by the relative numbers of local, in-state, regional, or national students, which is substantially a function of socioeconomic status. The language of Zemsky & Oedel (1983, pp. 11–12, quoted above) suggests that geomarket borders within large metropolitan areas may have been drawn in ways that separate affluent from less affluent communities. We present the following hypothesis:

H1. In large metropolitan areas that contain multiple geomarkets, we expect significant socioeconomic inequality (e.g., income, parental education) between geomarkets.

We expect substantial racial inequality between geomarkets in large metropolitan areas for several reasons. Interestingly, the Market Segment Model is explicitly based on socioeconomic stratification, but Zemsky & Oedel (1983) do not mention race once. U.S. cities are characterized be extreme historic and contemporary residential racial segregation (Korver-Glenn, 2022). Structures built upon racialized structures are racialized structures. 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, geomarket borders may have been drawn along class divides. A strong correlation exists between race and wealth (Kraus, Onyeador, Daumeyer, Rucker, & Richeson, 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. Although these arguments are speculative, the extent of racial inequality between geomarkets can be assessed empirically. We present the following hypothesis:

H2. In large metropolitan areas that contain multiple geomarkets, we expect significant racial inequality (e.g., income, parental education) between geomarkets.

The Market Segment Model and Geomarkets raise concerns common to the application of correlations. The data on 1980 SAT score-sending behavior analyzed by Zemsky & Oedel (1983) can be conceived as training data. These training data defined the Geomarkets in that the number of geomarkets created in a metropolitan area was based on the number of test-takers (Zemsky & Oedel, 1983). The training data identified student characteristics correlated with the local, in-state, regional, and national market segments. These analyses found that student demand for different kinds of colleges was largely a function of social origin, and that student demand within a Geomarket was largely a function of the class composition of the Geomarket. However, Zemsky & Oedel (1983) did not interrogate the historical and contemporary structural inequalities that produced observed patterns of social stratification. Instead, the Market Segment Model encouraged colleges to use this snapshot of student demand as the basis for future decisions about which communities and prospective students should be targeted by college recruiting campaigns. This process exeemplifies the "ratchet effect" (Harcourt, 2015), whereby predicting the behavior of future individuals based on the behavior of past individuals "threatens to reify and reporduce existing inequalities" (Burrell & Fourcade, 2021, p. 224). This process also exemplifies concerns about proxy variables, whereby selective colleges view privileged social class as a proxy for desirable students. This creates an incentive to focus recruiting efforts on communities that have these characteristics. Zemsky & Oedel (1983, p. 44) discuss these concerns:

> On occasion, senior spokespersons for the profession worry that students outside the main 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.

Commodification of the Market Segment Model and Geomarkets "engineers homophily" (Chun, 2021). In itself, the Market Segment model is a "stylized fact" (Hirschman, 2021) about the structure of student demand, one that does not consider historic structural inequalities that produced observed patterns. Once the College Board inscribed the Market Segment Model and Geomarkets into the EPS product, this product may amplify the effect of historic structural inequalities on future opportunity structure; a snapshot of extant stratification in student demand becomes the basis for college decisions about which local markets to target.

Utilization of the EPS product raises concerns about the quantification themes of reactivity, discipline, and authority (Espeland & Stephens, 2008). 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. We suggest that EPS disciplines 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 by, first, choosing which Geomarkets to recruit from – those with a large number of prospects from the desired market segment – and, second, informing which high schools to visit within these Geomarkets. Under the principle of homophily, 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-driving framework – The Market Segment Model – replicated 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, use of EPS contributed to most colleges visiting the same sets of affluent, high-achieving high schools.[9]

3.1 Geomarket Filter in Student Search Service

In XXXX, College Board Geomarkets were incorporated as a search filter in the College Board 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

[9]We were told that savvier EPS users visited high schools that EPS recommended not visiting because there would be less competition for the good students that attended these high schools.

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. 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. 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 (Author, XXXX).

Student lists are positively associated with student outcomes. A College Board research report by Howell, Hurwitz, Mabel, & Smith (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. 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%).[10] 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.[11]

[10]Leveraging a natural experiment in College Board student list purchases, Smith, Howell, & Hurwitz (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.

[11]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%).

However, Jaquette & Salazar (2024) argue that student list products exacerbate racial inequality in college access. Jaquette & Salazar (2024) 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 (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). Products built upon structural racism are structurally racist products. Student list products offer many geographic filters. Some geographic filters are based on known geographic borders (e.g., zip code, county, CBSA, state). Additionally, the College Board created geographic borders that subsequently became filters in the *Student Search Service*.[12] Geomarket search filters, slice states and metropolitan areas into smaller, local recruiting markets. 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 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) provides recommendations about how The Market Segment Model and Geomarkets should be utilized in the context of purchasing student lists. The Market

[12] For example, the 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).

Segment model "simply demonstrates 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" (p. 42). The authors describe a college that "draws most of its students from regional or national segments" (p. 42). Focusing on New England – including the Boston Geomarket, which was relatively low-income in 1980 – the authors ask, "where would you concentrate your energies" (p. 42),

> 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 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 three of the four communities in the bottom band, Manchester, Hartford, and Fairfield County. Simply by knowing a little bit about the students' backgrounds and academic records you could quickly focus your attention on those most likely to consider your kind of institution. 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" (p. 42-44)

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). 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 targeted by this strategy are disproportionately enrolled in affluent, predominantly white schools.

4 Data and Methods

4.1 Data and Variables

Research question 1, data. RQ1 asks, what is the socioeconomic and racial variation between Geomarkets in metropolitan areas? And, how does this variation change over time? To answer this question, we use census tract-level data from the US Census Bureau. Census tract is the smallest geographic area for which measures of both race/ethnicity and socioeconomic characteristics are available. Utilizing a small geographic area is important for implementing a spatial merge between Census data and Geomarket shape files, described below.

We utilize data from the 1980 Decennial Census, specifically variables from Summary Tape File 1 (STF1), which contains data from the about race and hispanic origin from the "short form" questions answered by all households and data from Summary Tape File 3 (STF3), which contains data about socioeconomic characteristics – including income, education, and poverty – derived from 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. In order to examine how the characteristics of Geomarkets changed over time, we utilize tract-level data from the 2000 Decennial Census, similarly using data from Summary File 1A (SF1A) to obtain measures of race and Hispanic origin and using data from Summary File 3A (SF3A) to obtain measures of income, education, and poverty.[13] Beginning in 2010, the Decennial Census no longer collected a "long form" questionnaire. These questions were replaced by the American Community Survey (ACS). We also utilized data from the 2020 5-year ACS, which includes data collected from 2016-2020.[14] This data collection period mirrors the period for our primary data collection about student list purchases used to analyze RQ2, as described below.

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

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

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.[15] Essentially, the data 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 shapefile 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 shapefiles. Census tract shapefiles that intersected with multiple Geomarkets were 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.

Research question 1, variables. RQ1 asks, what is the socioeconomic and racial variation between Geomarkets in metropolitan areas? And, how does this variation change over time? We created measures of race and ethnicity, specifically the number and proportion of people (all ages) 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+ races, non-Hispanic. Measures of XXX were not available for 1980 Decennial Census. We also created socioeconomic measures that approxmiate the predictors of market segment identified by Zemsky & Oedel (1983). These variables are median household income, mean household income, percent of households below the poverty line, and people age 25+ with a BA.[16] All measures were created at the census tract-level and the Geomarket-level by aggregating tract-level data to Geomarkets.

[15]The author of the post reported that he found the zip codes associated with Geomarkets from a Google search.
[16]STATE THAT MEAN HOUSEHOLD INCOME CREATED BY DIVIDING AGGREGATE INCOME BY NUMBER OF PEOPLE. NEED FIX THIS MEASURE THO.

Research question 2, data. Geomarket is a search filter available in the College Board Student Search Service product. RQ2 asks, how does the racial and socioeconomic composition of included versus included prospects vary when student list purchases filter on particular 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 CA, IL, MN, and TX. Utilizing public records requests to obtain public records is a painstaking process. Initially, the majority of universities did not respond to our request or denied our request. Subsequently, we obtained pro bono representation from four law firms, which substantially increased the success of data collection. We 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 TX.

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 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 a third-party consulting firm. 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.

This article analyzes student lists purchased from College Board. We exclude student list purchases by MN public universities from this report because Minnesota is predominantly an "ACT state."

14 public universities provided PDF order summaries containing the search criteria for 830 student list purchases. We utilized the XXXX Python/R package to convert these order summaries into tabular data. About 16% of student list purchases utilized the Geomarket filter.

We received both (a) the order summary data and (b) the de-identified prospect-level student list data for 414 orders associated with 2,549,085 prospects. We draw from these data to answer RQ2. 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]. 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 RQ2 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 answer RQ2 by simulating which prospective students would have been included or excluded from the student list purchase had the purchase filtered on partiulcar Geomarkets.

Research question 2, variables. The variables of interest for RQ2 the characteristics of prospective students who would have been included/excluded by our simulations and the characteristics of their schools and neighborhoods. Prospect characteristics are derived from the pretest questionnaire administered to College Board test-takers. The de-identified student lists we received contain a standard subset of variables (e.g., HS code, HS GPA range, intended major). We create detailed measures of race and ethnicity. Information about student socioeconomic status is limited. However, we create a measure of whether the prospect is first-generation college student. We can also measure the socioeconomic characteristics of the students' home zip code and characteristics of their high school [EXPAND OR DELETE THIS SENTENCE DEPENDING ON WHETHER WE USE THESE DATA].

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

4.2 Methods

Research design. We utilize a multiple, quantitative case study design in which metropolitan areas are cases. Following XXX [CITE], we focus on a small number [HOW MANY] of metropolitan areas in order to provide sufficient analytic depth while also situating each case within the context of historic segregation and contemporary gentrification. Online Appendix XXX presents results for a larger number of metropolitan areas.

Choice of metropolitan areas is informed by several factors. Based on our read of Zemsky & Oedel (1983), we are interested in "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). Building on our conceptual framework, we are interested in racial and socioeconomic inequality between geomarkets within a metropolitan area (RQ1) and how this inequality contributes to inequality in which prospective students are targeted by student list purchases (RQ2). [DISCUSSION OF WHICH CASES TO SELECT. KARINA]. Choice of metropolitan areas is informed by data availability. Although Census data are available for all metropolitan areas (RQ1) we do not have good candidate student list purchases for all metropolitan areas (RQ2). [SAY SOMETHING ABOUT WHAT IS A GOOD CANDIDATE STUDENT LIST PURCHASE – PURCHASE WITH NOT TOO MANY CRITERIA THAT INCLUDE ALL GEOMARKETS IN A METRO].

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. For example, in the San Francisco Bay Area, how does the City of Oakland Geomarket (CA07) differ from the Alameda County Exluding Oakland Geomarket (CA08). 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. Interactive maps provide a more granual visualization of where prospects lived and went to high school. For example, for purchased profiles who lived in the Chester County Geomarket (PA02) [OR PHILADELPHIA PA05] and identified as Black, where in the county did these students live and which high schools did they attend?

NEXT STEPS: CREATE TABLE FOR PHILLY STUDENT LIST PURCHASES THAT FOCUSES ON FIRST GEN STATUS.

Our conceptual framework suggests that racial and socioeconomic inequality is Geomarket regions is associated with the number of geomarkets in the metropolitan area. and is associated with the patterns of racial segregation in the metropolitan area. comment more on this.

Below, we use simulations and actual student list purchases that filtered on geomarkets. In purchases that filtered on test-score and/or GPA thresholds, we can simluate who would be included and excluded had certain Geomarkets were been selected. In purchases that filter on geomarkets, we can get an initial sense of who is included in geomarkets targeted by regional state colleges versus research universities.

5 Discussion

In their analysis of quantifying school quality in England, McArthur & Reeves (2022, p. 517) observe that "one problem with school league tables …is that the measures of school quality often merely reflect the social origins of those who attend a particular school." Similarly, considering prior research showing that SAT scores are substantially a function of social origin (Sewell & Shah, 1967), the Market Segment Model argues that student demand for higher education is mostly a function of social origin.

Institutional theory defines the organizational field 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 and products" (DiMaggio & Powell, 1983, p. 143).

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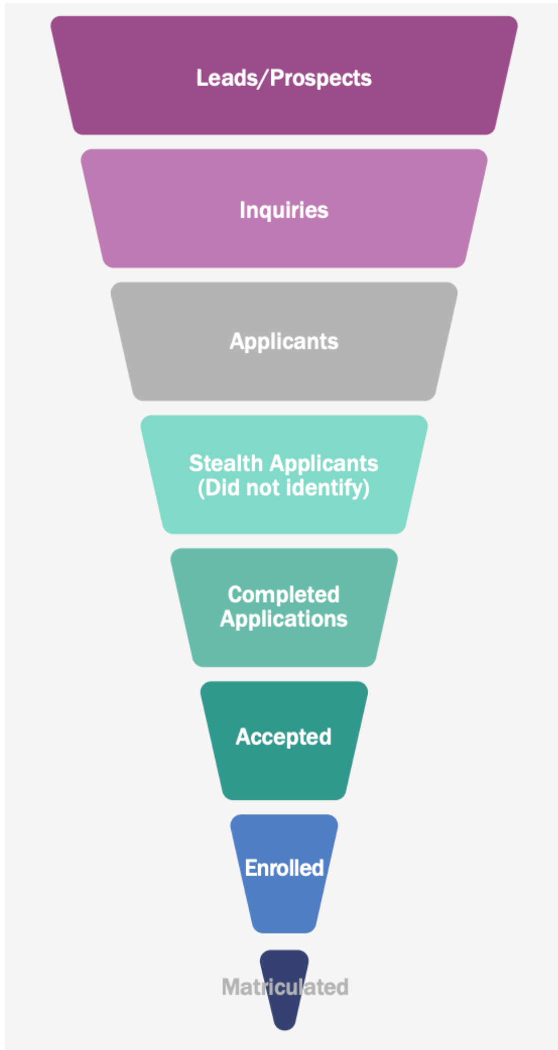

Figure 1: The Enrollment Funnel

A Appendix A

Table A1 reproduces a partial, simplified version of the bottom panel of Zemsky & Oedel (1983, fig. 2.1) which represents the Market Segment Profile for "Connecticut Market 3: Fairfield County." Table A1 has separate columns for each market segment (local, in-state, regional, national) and rows show the number of test-takers and characteristics of test-takers. For example, there were 550 "local" students in Fairfield county and these students submitted SAT scores to 2.8 postsecondary institutions on average. By contrast, there were 1,664 "regional" students who submitted test scores to 4.8 institutions on average. For local students, 11.2% had family income greater than $35,000 and 9% had both parents with a BA. For regional students, 41.9% had family income greater than $35,000 and 34.0% had both parents with a BA. Each Market Segment Profile also present information about the institutions that students from each segment sent scores to.

Table A2 recreates the top panel of Zemsky & Oedel (1983, fig. 2.1) for the Fairfield County, CT local market. For example, of the 550 local students, 277 (50.4%) sent scores to institution #1, which was a private master's granting institution. Of the 1,199 in-state students, 757 (63.1) sent scores to institution #1, a public doctoral granting institution, and 515 (43.0%) sent scores to institution #2, a public master's granting institution.

The *Institutional Profile* describes students who send scores to a particular institution and which majors these students are interested in. For each institution, institutional profiles are created separately for students from a particular local market, for all students in a state, or all students in a region. Table A3 reproduces a partial, simplified version of Zemsky & Oedel (1983, fig. 2.3), the institutional profile of an anonymous institution for students from Fairfield County, CT. Table A3 shows that 58 in-state students submitted SAT scores to the institution. These 58 students represented 4.8% of the total 1,199 in-state students from Fairfield County. 69 regional students sent scores to the institution, representing 4.1% of all 1,664 regional test-takers. Of these 69 regional students, 35 expressed interest in majoring in the liberal arts. These 35 students represent 7.0% of all regional students from Fairfield County who expressed interest in the liberal arts.

Zemsky & Oedel (1983) argue that the Institutional Profile and the Market Segment Profile enable admissions officers to know where to look for students and which institutions are competing for those students (p. 25):

> The Institutional Profile and the Market Segment Profile quantify the admission officers' intuitive grasp of market structure. Structure here carries a dual meaning, connoting both the structure of student choice and the structure of institutional competition...This two-sided interpretation furnishes the essential framework for planning by individual colleges and universities...To draw effectively on its own natural constituency, a college not only must contact the "right" kind of students — that is, students who are predisposed toward that type of institution – but also must persuade them of its special character. This means knowing the competition as well as the clientele.

Table A1: Simplified market segment profile, Connecticut Market 3: Fairfield County

Characteristic	Local	In-state	Regional	National
Total test takers	550.0	1199.0	1664.0	3766.0
Avg SAT (verbal + math)	770.0	850.0	970.0	980.0
Avg # scores sent per test taker	2.8	3.5	4.8	5.3
Percent in top 20% of HS class	27.8	26.1	44.7	45.7
Percent aspiring to more than BA	30.6	41.5	54.5	62.2
Percent family income more than $35,000	11.2	20.6	41.9	43.0
Percent both parents with BA	9.0	16.3	34.0	37.1

Table A2: Top 5 institutions in terms of number of scores sent by segment, Connecticut Market 3: Fairfield County

	Local (N=550)			In-state (N=1,199)			Regional (N=1,664)			National (N=3,766)		
	Num	Pct	Type	Num	Pct	Type	Num	Pct	Type	Num	Pct	Type
1	277	50.4	priv ma	757	63.1	pub doct	610	36.7	pub doct	1226	32.6	pub doc
2	261	47.5	priv ma	515	43.0	pub ma	348	20.9	priv doct	371	9.9	priv doct
3	183	33.3	priv ma	438	36.5	pub ma	272	16.3	priv doct	327	8.7	priv res
4	103	18.7	pub doct	183	15.3	pub ma	248	14.9	pub doct	312	8.3	priv doct
5	100	18.2	pub ma	177	14.8	pub ma	197	11.8	pub doct	308	8.2	priv doct

Table A3: Simplified sample institutional profile for anonymous institution, students from Connecticut Market 3: Fairfield County

	Local	In-state	Regional	National	Total
Total number of scores received	1.0	58.0	69.0	109.0	237.0
Pct of all test-takers in segment	0.2	4.8	4.1	2.9	3.3
lib_arts_num	0.0	25.0	35.0	61.0	121.0
lib_arts_share	0.0	8.4	7.0	5.3	5.9
engineering_num	0.0	2.0	5.0	3.0	10.0
engineering_share	0.0	3.0	5.8	0.8	1.8