Disruptive Interactions:

Long-run Peer Effects of Disciplinary Schools*

A. Yonah Meiselman†

Anjali P. Verma‡

(Job Market Paper)

October 14, 2021 | Latest Version

Abstract

Evidence suggests that exclusionary discipline such as temporary removal of students to disciplinary alternative schools, has an adverse impact on students' long-run outcomes. This paper provides one of the first pieces of evidence for a potential channel — namely, *disruptive peer effects* at disciplinary alternative schools — driving adverse effects among removed students. To study this, we use the restricted administrative records of all high school students in Texas public schools with a disciplinary placement between 2004 to 2018. Given that a large number of regular schools send their disruptive students to a single disciplinary alternative school, we exploit the idiosyncratic variation in peer composition within a disciplinary school to estimate the effect of peers' disruptiveness on students' outcomes. Results show that having peers' with higher average disruptiveness when placed at a disciplinary schools leads to, 1) an increase in students' subsequent disciplinary removals, 2) decline in educational attainment – lower high-school graduation, college enrollment, and college graduation, and 3) decline in labor market outcomes – lower employment and earnings ($\sim$ 8% or 1272 USD decline in annual earnings at age 27). Given the lasting negative effects of peers at disciplinary schools, these results highlight the need to examine exclusionary disciplinary policies, and adopt approaches that can mitigate the adverse impact of peers on students placed at these schools.

*We are grateful to Richard Murphy, Stephen J. Trejo, Mike Geruso, Tom Vogl, Nishith Prakash, Sandra E. Black, and Vinayak Iyer for their constant guidance and feedback, and all seminar participants at UT-Austin for their helpful comments and suggestions. We also thank Texas ERC to generously provide the data. *Disclaimer:* The conclusions of this research do not necessarily reflect the opinion or official position of the Texas Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas.

†Akiva Yonah Meiselman: Department of Economics, University of Texas at Austin.

‡Anjali Priya Verma. Department of Economics, University of Texas at Austin.

I. Introduction

School discipline is a central topic of debate in policy discussions, ranging from 'zero-tolerance policies' of early nineties to the Obama administration's 'Dear Colleague Letter' guidelines on school discipline.[1] Disruptive students impose both a direct cost on regular students and teachers in school, and an indirect long-term cost on society through an increased propensity of being unemployed or committing crimes as adults. Therefore, to impart discipline and meet the educational needs of these students while maintaining safe school environments, schools have increasingly relied on the temporary removal of disruptive students to disciplinary alternative schools. However, a growing body of literature suggests that disciplinary removal facilitates the so-called 'school-to-prison pipeline', according to which exclusionary discipline pushes students out of the school system through increased dropouts, leads to adverse future outcomes, and increases their risk of incarceration as adults (Bacher-Hicks, Billings and Deming, 2019; Marchbanks III et al., 2015; Rumberger and Losen, 2017).[2]

In this paper, we provide one of the first causal evidence on a potential channel – namely, *disruptive peer effects* at disciplinary alternative schools, explaining worse future outcomes among students who are removed to these schools. Social interaction and peer effects play an important role in determining an individual's behavior and economic outcomes.[3] Becker (1996); Durlauf et al. (1997) argue that the propensity that an individual behaves in a particular way is positively associated with the prevalence of such behavior in their peers. Similarly, Bayer, Hjalmarsson and Pozen (2009) show an increase in criminal recidivism among inmates who are

[1] The term zero tolerance was first employed by President Ronald Reagan's administration in an attempt to eradicate drug possession and drug use on school property. However, the policy became law when Congress passed the Drug-Free Schools and Campuses Act of 1989, and Gun-free Schools Act of 1994. Although originally intended as a response to serious offenses (e.g., selling drugs or engaging in gang-related fights on school grounds) to ensure safe and healthy schools, in recent years zero tolerance policies have been applied broadly to include minor offenses (e.g., talking back to school personnel, bringing over the counter or prescription drugs on school grounds without a doctor's note, and coming to school out of uniform). On the other hand, concerned by the growing negative effects of strict exclusionary discipline policies, Obama administration passed the 'Dear Colleague Letter' guidelines – the first national guidelines on school discipline to ensure safe schools while addressing disciplinary policies and practices that can put students out of school and into the justice system. The guidelines urged schools to remove students from classrooms for disciplinary reasons only as a last resort becomes of the .

[2] According to U.S. Department of Education, Health and Human Services (2014), students who are removed are as much as 10 times more likely to drop out of high school, experience academic failure, and face incarceration than those who are not.

[3] There is vast evidence for the prevalence and importance of social interactions and peer effects in a wide variety of settings, ranging from schools (Black, Devereux and Salvanes, 2013; Carrell, Hoekstra and Kuka, 2018; Hoxby, 2000; Lavy and Schlosser, 2011; Murphy and Weinhardt, 2020), workplace (Guryan, Kroft and Notowidigdo, 2009; Rosaz, Slonim and Villeval, 2016), in criminal behavior (Bayer, Hjalmarsson and Pozen, 2009), program participation (Dahl, Løken and Mogstad, 2014), retirement and work decisions(Duflo and Saez, 2003; Field et al., 2016), among others.

exposed to other inmates with a history of the same crime.

Disciplinary alternative schools expose students to a concentrated group of other disruptive students. Hence, when disruptive students are placed at these schools, it can reinforce and exacerbate disruptive behavior among students, leading to adverse impact on their future outcomes (Dishion, McCord and Poulin, 1999; Van Acker, 2007). We analyze the impact of having a more disruptive versus a less disruptive peer group during a student's first disciplinary placement on their subsequent removals, educational attainment, and long-run labor market outcomes. Given the evidence of a link between disciplinary placements and adult incarcerations, it is important to understand the extent to which peer effects at disciplinary schools can contribute to this relationship.

To study this, we utilize the setting of Disciplinary Alternative Schools in Texas, commonly known as Disciplinary Alternative Education Programs (henceforth DAEPs). DAEPs are temporary schools for disruptive students who are removed from their regular instructional schools and provide educational settings to these students during the removal period. Unlike suspensions which relate to minor misbehavior and last between 1-3 days, DAEP placements correspond to more serious misbehavior and are long-term removals (on average 1-3 months). Since there are a limited number of DAEPs per school district, each DAEP admits students from a large number of regular schools. This means, the peer composition at a DAEP is determined by : 1) the set of students who are removed from various sending schools at that point in time and 2) the duration of DAEP placement for each student. We utilize this over-time variation in peer composition with a DAEP to study the impact of peers' disruptiveness on students outcomes. While our setting is similar to cohort-to-cohort variation approach that is commonly used in the peer effects literature (Bifulco, Fletcher and Ross, 2011; Black, Devereux and Salvanes, 2013; Gould, Lavy and Daniele Paserman, 2009; Hoxby, 2000; Vigdor and Nechyba, 2007), there are a few added advantages of our setting. First, in the context of regular schools, a common concern is that parents may choose schools based on the average peer composition, resulting in endogeneity of peer composition.[4] However, this is less of a concern in our context as sending schools are constrained by the limited availability of DAEPs in a school district. Secondly, since

[4] To address this, most studies either rely on instrumental variable approach, or use natural experimental settings (Guryan, Kroft and Notowidigdo, 2009; Sacerdote, 2001).

students are sent to DAEPs for a limited duration (unlike schools where the peer composition is fixed for most of the school year), this generates additional variation based on peers' placement durations (which is determined independently by each sending school).

We use restricted state administrative data of all high school students in the Texas public system between 2004 and 2018 who are ever placed in a DAEP. This data provides us a unique, high-quality individual-level records of students' academic and demographic information, and also tracks each students' higher education and labor market outcomes. Importantly, this is one of the few datasets that provides a detailed record of each student's discipline data, including information on the date of student placement at a DAEP, placement duration, DAEP identifier, each suspension record, reasons for removal etc.

The main analysis sample consists of all high school students in Texas who are placed at a DAEP for the first time.[5] For each student, peers are defined as the set of all other high-school students (excluding the student herself) present in the same DAEP during the student's placement window. We proxy for peer's disruptiveness by their average yearly suspensions in the past.[6] Using this, we create a continuous measure and a quintile measure of peers' average disruptiveness (such that highest quintile being the most disruptive) for each student in the main analysis sample.

For our empirical strategy, we leverage the idiosyncratic residual variation in average peer's disruptiveness after controlling for DAEP $\times$ year FEs, school-term FEs, reason for removal FEs, and DAEP $\times$ duration-bin FEs. This means we are effectively comparing students who are removed for similar reasons and similar duration-bins, and identifying the treatment effect off the within-year variation in peers' disruptiveness in a DAEP.

Causal interpretation of peer effects in our setting relies on the assumption that after controlling for the fixed effects, residual variation in peers' disruptiveness is as good as random. We test the validity of this assumption by performing a balance test between peers' disruptiveness and students' pre-determined demographic, academic, and disciplinary characteris-

5 Student's exposure to other disruptive students not only reinforces disruptive behavior but also has a cumulative effect on future disciplinary placements. To avoid the endogeneity arising from this, we restrict the student sample to only those who are placed at a DAEP for the first time.

6 Unlike DAEP placement which are longer term removals and used only in case of serious misbehavior, suspensions occur for less than 3 days, and are used very frequently to deal with student's misbehavior.

tics. Estimates from this test show that peer's disruptiveness does not significantly predict pre-determined student characteristics and therefore, the treatment effect in our setting can be interpretation as causal.

For our main results, we estimate the impact of peers' disruptiveness on three broad sets of students' outcomes – 1) subsequent disciplinary removals, 2) educational attainment, and 3) labor market outcomes. For disciplinary outcomes, we find that having a more distuptive peer group during the DAEP placement, leads to an increase in future suspensions and DAEP placements for the students. Moving students from to Q1 (lowest quintile) to Q5 (highest quintile) in peers' disruptiveness leads to a 5 percent increase in future suspensions and an 8.5 percent increase in future DAEP placements, per year. These results show that more disruptive peers at DAEPs reinforce disruptive behavior among students and increase their future disciplinary recidivism. An increase in future removals implies an increase in the amount of time spent outside regular classrooms as well as repeated interaction with other disruptive students at DAEPs. Both these factors can push marginal students even further and increase their chances of dropping out of school. Consistent with this, we find that relative to Q1, having peers in Q5 of average disruptiveness leads to 6 percent lower high-school graduation, 7 percent lower college enrollment and 17 percent lower college graduation. To understand this impact better, we consider enrollment and graduation from two-year and four-year college separately, and find that most of our effects are driven by two-year colleges.[7]

Higher education is a strong determinant of an individual's labor market outcomes. For analyzing labor market outcomes, we look at two main indicators - annual quarters of employment and average annual earnings. Estimates show that having more disruptive peers (Q5 relative to Q1) during a student's DAEP placement results in 2.5 percent lower quarters of employment and 6.5 percent ($\sim$ \$800) lower earnings at age 23-27. We further dissect this impact by each age group and find that the decline in earnings increases with age. Using the \$1272 decline in annual earnings at age 27 as the lower bound of the mean differences in annual earnings beyond 27, we estimate a net loss of \$33,484 in present discounted value of lifetime income

[7] 90 percent of college enrollment in our sample corresponds to two-year college. This makes sense as students in our sample come from the lower part of the ability distribution and hence, are less likely to enroll or graduate from four-year college.

from having a more disruptive peer group at DAEPs during school.

These findings are robust to a series of robustness and specifications tests, including addition of more controls and fixed effects, using a different measure of peers' disruptiveness, alternative matching on peers, as well as randomization inference.

We further go on to explore the determinants of peer effects beyond the average disruptiveness. We find that peers' disruptiveness has a larger impact on students' outcomes 1) when majority of the peers are removed for a similar reason as the student and 2) when the distribution of disruptiveness among peers is more concentrated than dispersed around the mean. This means peer effects are stronger when students have similar peers in terms of disruptive characteristics and receive more consistent reinforcement.

The paper makes three broad contributions to the literature. First, to the best of our knowledge, this is one of the first papers to show a potential channel — namely, reinforcing peer effects — as an underlying mechanism connecting student removal and worse long-run outcomes. Past studies on the impact of student removals are descriptive in nature and do not provide causal estimates (Fabelo et al., 2011; Marchbanks III et al., 2014, 2015). Our paper shows the causal impact of peers' disruptiveness at DAEPs on students' short-run and long-run outcomes, including labor market outcomes. Our study also contributes to the growing literature on school disciplinary policies such as policing at schools, the impact of suspensions (Bacher-Hicks, Billings and Deming, 2019; Weisburst, 2019). We add to this literature by estimating effects that arise from a different disciplinary policy i.e. temporary placement of disruptive students at alternative schools. A history of disciplinary referrals and placement at alternative schools have been argued to be amongst the most important contributors to the school-to-prison pipeline (Appleseed, 2007)[8], and hence, it is important to understand the underlying channels driving this relationship. We show that disruptive peers at DAEPs increase students' future removals, school dropouts, and lowers wages, and thus can explain a part of the impact of exclusionary discipline.

[8] School-to-Prison Pipeline refers to a set of school practices that funnel youths from schools into the justice system. The pathways include a combination of policies that (i) removes students from their regular classrooms, such as suspensions and alternative school placements, and (ii) criminalizes student misbehavior, leading to school-based arrests and ticketing. This pushes students out of the school system, with the last segment of the pipeline leading to adult prison.

Second, this paper contributes in several ways to the literature on peer effects – Ours is one of the few papers that documents long-run peer effects from a short-term interaction. There is very little literature that shows the impact of peers on long-run outcomes. However, papers that do show evidence for long-run effects study the impact of a relatively more sustained peer group – for example interaction with classmates in a regular school over the entire academic year or several years (Carrell, Hoekstra and Kuka, 2018; Denning, Murphy and Weinhardt, 2020). Moreover, a vast majority of literature show peer effects on short-run outcomes (Black, Devereux and Salvanes, 2013; Hoxby, 2000; Sacerdote, 2001)). In contrast to these, DAEP placements are temporary removals and hence on average lasts between 1-3 months. Thus, using this setting along with the linked administrative data from Texas that follows students' up to their labor market outcomes adult, we document the long-run effects of peers from a relatively short-term interaction.

Existing evidence on disruptive peer effects shows the negative effects of having disruptive peers in a classroom on outcomes of the regular students (Carrell and Hoekstra, 2010; Carrell, Hoekstra and Kuka, 2018; Gaviria and Raphael, 2001; Lavy, Silva and Weinhardt, 2012). We extend this literature by providing evidence on the impact of disruptive peers on outcomes of disruptive students in the context of DAEPs. Disruptive students are more likely to be marginal and at-risk students. Our results highlight that exposure of these students to other disruptive students at DAEPs can further push these students off the margin and adversely impact their long-run outcomes. Additionally, our paper also contributes evidence on reinforcing peer effects. In the context of juvenile correction facilities in Florida, (Bayer, Hjalmarsson and Pozen, 2009) shows that when inmates are exposed to peers with a history of the same crime it leads to an increase in crime-specific recidivism. Consistent with this, our paper shows that when disruptive students are exposed to a concentrated group of disruptive peers, it leads to a reinforcement of disruptive behavior among students reflected by an increase in future removals.

Third and more broadly, we contribute to the growing literature that documents the impact of childhood interactions and the local environment on adult-life outcomes. This includes impact of factors such as residential neighborhoods during childhood (Chetty, Hendren and Katz, 2016; Chyn, 2018), pupil-teacher ratio (Dearden, Ferri and Meghir, 2002), teacher's quality (Chetty et al., 2011), presence of disruptive peers in classroom (Carrell, Hoekstra and Kuka, 2018), peers' racial composition in classrooms (Johnson, 2011), among others, as a determinant of adult outcome. We contribute to this literature by showing that disruptive peer effects at a DAEP when in school can have a long-term impact on the student's adult earnings in the mid-to-late twenties.

The rest of the paper is organized as follows: Section II lays out the settings for this paper, section III describes the data and descriptive statistics, section IV presents the empirical strategy and test for identifying assumption, section V presents the main results, section VI test for the robustness of the main findings, section VII shows supplementary results, section VIII contextualizes the results, and IX discusses the policy implications and concludes.

II. Setting: Disciplinary Alternative Schools in Texas

Before the 1990s, students whose behaviors were considered delinquent or disruptive to the extent requiring removal from regular classrooms were either suspended or expelled to the streets. However, since adoption of the Texas Safe Schools Act in 1995, all Texas public school districts have been required to provide disciplinary alternative schools for students removed for more than a few days.[9] Disciplinary alternative schools provide a separate settings for disruptive students who are removed from their regular instructional settings, often as an alternative to suspension or expulsion. While each school district is required to have their own DAEP, in some cases two neighboring school districts can tie-up and place their students into a single DAEP. Disciplinary alternative schools function around three main objectives - 1) to provide strict, controlled environment for disruptive students that can help inculcate self-discipline and correct inappropriate behavior 2) to provide continuity in instruction when the students are removed from their regular instructional setting, and 3) to improve the percent of attendance for students who would normally be withdrawn for lack of attendance. Unlike suspension which commonly lasts between 1-3 days, placement duration at disciplinary schools can range

[9] Since the passing of the Gun-Free Schools Act in 1994, there was a movement towards adoption of stricter school disciplinary policies to provide a safe and positive learning environment in the US. This led to the adoption of a "zero-tolerance" policy in school districts across the nation. While this policy was originally aimed at drastic violent crimes, over time strict disciplinary policies covering a wide range of student misbehavior were loosely packaged under the umbrella of "zero tolerance", which varied from state to state. In addition, states also varied in how they deal with the removed students, with a majority of states requiring alternative educational assignments for removed students (Appleseed, 2018).

anywhere between a few days to a few months or an entire school semester. This is so because disciplinary schools specifically serve students with more serious disciplinary acts and are deemed disruptive to the education and safety of other students in their original schools (Aron and Zweig, 2003; Kleiner et al., 2002).

Peer composition at disciplinary schools. DAEPs provide a very apt setting to study peer effects as there are only a few DAEPs per school district. In 2016, Texas had 1231 school districts and only 967 DAEPS i.e. on an average less than one DAEP for all schools within a district. This means on average, at any given time, peer composition at a DAEP is composed of a mixture of students from many sending schools. This provides over-time variation in peer composition within a DAEP that is not 1:1 reflection of the peer composition at regular schools. Figure 1 plots a map of all the schools within Austin ISD and corresponding alternate education campuses. Secondly, peer composition for a student i also depends on his/her date of placement as well as placement duration. This means, peer composition may change even if a student is placed for the same duration but at a different date or same date but for a different duration. This is so because the set of students who are placed from other sending schools may not be the same at a different date or duration of placement, and hence would change the relevant peer composition for student i.[10]

III. Data

III.A Student Administrative Data

This study uses the restricted Texas state administrative data provided by the Texas Education Research Centre (TxERC), that contains information from several state-level institutions.[11] For constructing the main sample, we use data from Texas Education Agency (TEA) on all high

[10] A common threat to exogeneity of peers in school choice literature arises if parents can choose where to send their kids conditional on the average peer composition. Our setting allows us to overcome some of these challenges as the decision to whether or not to send a student to a DAEP and for how long to send is decided independently by each student's sending school in the district. Thus, it is less likely that that decisions related to a student's placement and duration is conditional on the peer composition at a DAEP in that point in time.

[11] For more information on the ERC, visit https://research.utexas.edu/erc/

school students in the with a DAEP placement between 2004 and 2018.[12] This dataset provides longitudinal individual-level data for the entire population of K-12 students in the Texas public education system and contains detailed data on academic records, enrollment, attendance, and high school graduation. Importantly, this is one of the few datasets that provides high-quality discipline data for each disciplinary record at student-level. This includes data on students' DAEP placements, the date of placement, reason for removal, duration of placement, as well as DAEP identifier. This is crucial to our analysis as it allows us to identify the students placed at a DAEP and their relevant set of peers. For studying college outcomes, we use data from the Texas Higher Education Coordinating Board (THECB) which provides data on enrollment and graduation from all public institutions of higher education in the state of Texas. Lastly, employment and earnings data comes from the Texas Workforce Commission (TWC) that provides quarter level data on employment and wages of individuals in Texas.[13] We link all the three data sets to form a longitudinal panel of student-level data that links each student to their disciplinary records, higher educational outcomes, and follows them all the way till their adult labor market outcomes.[14]

Student and Peer Sample. Our main analysis sample consists of all high-school students who are placed at a DAEP for the first time. We only use students with first time placements for the main student sample as it is a clean sample – peer effects during their first placement can have an effect on the future placements too, and hence, any placement after the first one is endogeneous to the peer effects from his/her first DAEP placement. Next, for each student i in this sample, we define his/her peers as the set of all other high school students j ($j \neq i$), who are placed at the same DAEP during the student assigned placement duration. Thus, any student

[12] Our main sample consists of students in high schools between 2004-2018. Since the outcome data is limited to 2019, we will not observe all the students for medium and long-run outcomes. For those outcomes, we will restrict samples to individuals who can have mdeium and long-term outcomes till 2019. In addition, as a robustness check, we will also provide estimates from a consistent sample across all outcomes.

[13] This contains information of employment for all workers covered by Unemployment Insurance (UI).

[14] THECB and TWC only provides information on higher education or employment information within Texas. We are not able to observe any out-of-state enrollment, or out-of-state employment. However, this is less of a concern for several reasons: 1) Texas has the lowest out-migration rates among all states in the US (see, Figure A.15) and 2) Enrollment into out-of-state colleges is on average more difficult (competitively and financially) than for in-state colleges. Students in our sample come from the bottom of the ability distribution and are more likely to be economically disadvantaged, making out-of-state enrollment even more unlikely option for these students and

j who is placed at the same DAEP but does not overlap with i's placement duration would not be counted towards i's peers.

Measure of Disruptiveness. We proxy for peers' disruptiveness by their average count of yearly suspensions in the past.[15] Figure 3a shows the variation in the past suspension counts per year for peers in the sample. Using this, we build a quintile measure of peer's disruptive capital, separately for middle-school and high-school samples. Figure 3b shows the average yearly suspension count for peers in the past corresponding to each of the 5 quintile categories, where the highest quintile corresponds to the most disruptive peer groups and the lowest quintile to the least disruptive peer groups. Peers in the first quintile (Q1) have an average of 1-2 suspensions per year, whereas peers in the 5th quintile (Q5) have on average 6-8 suspensions per year. Quintile measure helps us in drawing a more qualitative understanding of the impact based on the distribution of peers' disruptiveness.

Sample Construction. For each student in high school between 2004-2018, the administrative TEA data provides the date of DAEP placement, assigned duration of placement, as well as DAEP identifier. Using the date of DAEP placement, we identify the set of students who are placed at a DAEP for the first time. This is our main student sample (i). Next, for each student in the main sample, we calculate their placement-window dates based on the placement date and assigned duration of placement. Then, using the DAEP identifier and the placement-window dates, we merge each student in the main sample with the set of all other high school students who were placed in the same DAEP and overlap with the student's placement-window. This set of all matched students is our Peer Sample (j).[16] Finally, to get a measure of peer exposure at student level, we allow each of i's observed peers, j, to contribute to this directly by the amount of overlap between peer j's placement with student i's placement duration. For each

[15] The number of past suspension counts can be correlated with the age of the peers too and we might be picking up some of the effect of age rather in addition to the disruptive capital of students. Hence, to eliminate this concern, instead of using total suspensions in the past, we use the number of past suspension counts per attendance year in the past. Note, we divide by the number of attendance years rather than the number of grades in the past since peers may not be part of the Texas Education system continuously for all the grades. In that case, we would not observe any suspension simply because they were not part of the sample

[16] Note that the set of peers doesn't include the student himself i.e. $j \neq i$

peer j, we calculate a peer weight, where peer weight is the proportion of his placement that overlap with student i's placement window. Using these peer weights, we aggregate the data at student level and generate the average peer characteristics for each observation in the main student sample. Thus our final sample consists of students with first time DAEP placements and the corresponding average peer characteristics.

III.B Descriptive Statistics

Table 1 shows the summary statistics for students and their peers in our sample. Column 1 shows the average characteristics of high school students who are placed for the first time at a DAEP, column 2 shows mean characteristics of peers in the sample, and column 3 shows the state average for all high school students in the Texas during this time period. Table shows that compared to state averages, DAEP population disproportionately represents blacks, hispanics, and economically disadvantaged students. Moreover, students in the DAEP are also more likely to be in the lower end of the ability distribution, and have significantly more number of yearly suspensions than an average student in Texas. This shows that students in the DAEP sample are systematically more marginal and at-risk students compared to regular students.

IV. Empirical Analysis

IV.A Empirical Strategy

For our empirical strategy, we leverage the idiosyncratic variation in average peer's disruptiveness after controlling for DAEP × year FEs, school-term FEs, reason for removal FEs, and DAEP × duration-bin FEs. This means we are effectively comparing students who are removed for similar reason and similar duration-bin, and identifying off the within-year variation in peers' disruptiveness in a DAEP.

We utilize the following empirical specification to estimate the impact of peers on students' subsequent outcomes:

$$Y_i = \beta \times \text{Peers' Avg Yearly Past Suspensions}_i + \theta_{dy} + \alpha_t + \gamma_{dl} + \delta_r + X_i + \epsilon_i \tag{1}$$

Y_i denotes outcome of outcome of student i, who is placed at a DAEP d, in year y and school-term t, for duration-bin l and reason r. *Peers' Avg Yearly Past Suspensions* denotes the measure of average peers' disruptiveness corresponding to student i. θ_{dy} is DAEP $\times$ year FEs and controls for any DAEP specific changes over time, τ_t is term FE that controls for any within year seasonality in student removal. γ_{dl} is DAEP $\times$ duration-bin FEs. This takes into account that across DAEPs there can be differences in student composition even for the same placement bin. δ_r is the reason for removal FEs. Finally, in the main regressions we also include a set of students controls denoted by X_i. This includes student's own past suspensions, previous test score, race, gender and sending-school removal rates.

To get a more qualitative picture of the outcome and to better interpret the results, we also construct a quintile measure of peer's average yearly past suspension counts such that higher quintiles correspond to more disruptive peers.

$$Y_i = \sum_{q=2}^{5} \beta_q \times \text{Quintiles of Peers' Avg Yearly Past Suspensions}_i + \theta_{dy} + \alpha_t + \gamma_{dl} + \delta_r + X_i + \epsilon_i \quad (2)$$

where *Quintiles of Peers' Avg Yearly Past Suspensions* is the quintile measure of peer's average yearly past suspension counts. The lowest quintile (q=1) is the omitted group. Thus, β_q estimates the impact of peers for each quintile relative to those in the lowest (first) quintile.

IV.B Identification

The two main threats to identification in the peer effects literature arises from the reflection and the selection problems. The reflection problem arises when it is difficult to disentangle whether disruptive peers at DAEPs affect a student's outcomes or whether the student negatively affects his peers (Manski, 1993). To overcome this problem, we use a measure of peers' disruptiveness based on their lagged disruptiveness i.e. peers' past suspension counts before the student's placement date. This also ensures that peers' measure of disruptiveness is pre-determined and hence not influenced by any correlated factors from current placement that can influence both peers' measure and students' outcomes.

Second, selection bias can arise if there is selection of students into peer groups that may be correlated with the outcome of interest. Causal interpretation of peer effects in our setting relies on the assumption that after controlling for the fixed effects, residual variation in peers' disruptiveness is as good as random. To test this, we conduct the balance test where we replace the outcome variable in the main specification by pre-determined student characteristics. Table 2 shows the estimates from this analysis. Each column corresponds to a separate regression with outcome denoted by the column header. Table shows the peer's disruptiveness is balanced across most of the observable student characteristics, and hence, assume the remaining variation in peers' disruptiveness to be orthogonal to observable factors that may determine our outcomes. Therefore, the estimates can be interpreted as the causal peer effects.

V. Main Results

V.A Impact on Subsequent Disciplinary Outcomes

Placement of students in a DAEP exposes them to a group of other disruptive students, which can have an adverse impact on their subsequent disruptive behavior. There are various suggestive evidence in the literature for this argument. First, being surrounded by a pool of disruptive peers can provide validation and reinforce disruptive behavior among students (Dishion, McCord and Poulin, 1999; Van Acker, 2007). Second, students can learn disruptive behaviour from their peers, resulting in increased future misbehaviors (Bayer, Hjalmarsson and Pozen, 2009). In addition, sociology and psychology literature points to the role of identity formation in affecting behavior. Peers' perception plays an important role in identity formation among teenagers, especially among disruptive students who face stigma from teachers and non-disruptive students. Levey et al. (2019) shows that when exposed to other delinquents, individuals show more delinquent behavior (moving towards group mean) to be identified as part of the group.

Hence, the first set of outcomes we analyze is impact of peers' disruptiveness on students' subsequent disciplinary outcomes. We focus on two main measures of disciplinary outcomes - future suspensions and future DAEP placements. Table 3 shows the impact of peers with 1 additional average annual past suspension. Column 1 shows impact on future suspensions per attendance year, which is calculated as total count of future suspensions divided by the number of future years that a student is observed in the sample. [17] Similarly, column 2 shows the impact on future DAEP placements per attendance year, calculated as the total number of future DAEP placements divided by the number of future years student is observed in the sample. In columns 3 and 4, we present results for sample of students with only non-zero future suspensions and DAEP placement.

Estimates across all 4 columns show that having peers with additional average yearly suspension in the past leads to significant increase in annual suspensions and DAEP placements in the future. In order to get a more qualitative understanding of the results, we also estimate the peer effects using the quintile measures for peers' disruptiveness. Figures 5a and 5b show the impact on future suspensions and DAEP placements using the quintile measure. Results show that compared to peers in Q1 of disruptiveness, having peers in Q5 (most disruptive) leads to 5 percent more suspensions per year, and 8.3 percent more DAEP placements per year in the future for students.[18] Thus, the results shows that when disruptive students are exposed to a group of other disruptive peers, it has a reinforcing effect on their future disruptive behavior.

Evidence suggests that students who are repeatedly referred to DAEPs are at a higher risk of dropping out of school in the future as well as contribute to the school-to-prison pipeline. Thus, if exposure to disruptive peers lead to an increase in the future suspensions and DAEP placements, it could have negative impacts on their future academic and labor markets outcomes too. Next, we explore the impact of peers at DAEPs on students' educational outcomes.

V.B Impact on High-school Graduation and College Outcomes

We study the impact of peers' disruptiveness at DAEPs on three main indicators of educational attainment- 1) high-school graduation, college enrollment, and college graduation. For these set of outcomes, the sample is restricted to individuals who are atleast of age 23 in the sample.

[17] We divide by the number of future attendance years instead to the number of future years in the sample to avoid any miscounting for students who drop out of school after the DAEP exit. Since student dropout is a worse outcome than student removal, our results on student removal can be thought as an underestimation of the adverse impact peers may have on students' subsequent disciplinary outcomes.

[18] Figures A.2a-A.2b plots this impact for samples with non-zero future suspensions and DAEP placement in the future, and show a similar trend.

Hence, the results can be interpreted as educational outcomes by age 23.

The first educational outcome we study is high-school graduation. Table 4 shows the impact of peers with 1 additional unit of disruptiveness, whereas figure 6a shows the impact for having peers in additional quintiles of disruptiveness relative to the lowest quintile. Results show that having more disruptive peers during a DAEP placement has a significant negative effect on a student's high-school graduation outcome. Relative to peers in Q1, having peers in Q5 (most disruptive) of peers' disruptiveness leads to 6 percent (3 pp) lower high-school graduation for students placed at these schools. The mean high school graduation for our sample is 54% compared to 87% for Texas. Thus on average students in our sample are farther from the margins of graduating from high schools. Results show that disruptive peers at DAEPs seem to push the marginal students even further away.

For higher education, we look at the impact on college enrollment and college graduation outcomes. For both the outcomes, we find that having more disruptive peers during DAEP placement is associated with significant decline in propensity to enroll and graduate from some college (see Table 4). Moving students from Q1 to Q5 of peers' disruptiveness leads to a 6.7 percent (2.3 pp) decline in their college enrollment (figure 7a) and approximately 17 percent (1.5 pp) decline in the college graduation (figure 7b). We further breakdown these outcomes by enrollment into 2-year and 4-year colleges (figures A.4a and A.4b), and graduation from 2-year and 4-year colleges (figures A.5a and A.5b). For both the outcomes, we find a significant decline corresponding to 2-year colleges, but not for 4-year colleges. This seems reasonable as the students in our sample less likely to enroll in a 4-year college as $\sim 90\%$ of college enrollment into correspond to a 2-year college. Moreover, measure of college readiness based on a statewide test also shows that the average college readiness among our sample is less than 50 percent.[19] Using college readiness as an outcome shows that exposure to disruptive peers at DAEPs leads to further decline in their college readiness (figure 6b).

Studies show that high-school and college graduates fare substantially better than their non-

[19] College readiness is an indicator (pass=1, fail=0) based on a statewide test called Texas Success Initiative Assessment (TSIA). The TSIA is part of the Texas Success Initiative enacted by the Texas State Legislature and designed to determine a student's readiness for college-level coursework in the general areas of reading, writing, and mathematics.

graduates on a wide variety of outcomes — on average, they are more employable, earn more money, are more likely to be married, and are less likely to go to jail than their counterparts. Thus, by adversely impacting educational outcomes, disruptive peer effects at DAEPs can have a negative impact on long term economic outcomes.

V.C Impact on Long-run Labor Market Outcomes

For labor market outcomes, we focus on two main indicators of labor supply - 1) employment and 2) earnings. To measure impact on employment, we use the total number of quarter employed per year at age 23-27, and for earnings, we look at the average annual earnings at age 23-27. For both the outcomes, we restrict samples to individuals who are atleast age 27 in the sample.[20]

Table 5 summarizes the impact on labor market outcome and shows that there is a significant negative impact of peers' disruptiveness on students' employment as well as earnigns. Figures 8a and 8b presents these results by the quintile of peers' disruptiveness. Relative to Q1, having peers in Q5 (most disruptive) leads to 2.5 percent decline in annual quarters of employment corresponding to an average of 2 quarters of employment per year. While the impact by quintiles are not statistically different from Q1, downward slope in avergae impact across quintiles reinstates the finding that there is a negative effect on employment as we move students from less disruptive to more disruptive peers.[21]

To understand the impact on earnings, we generate a measure of average annual earnings by summing up the quarterly earnings in each year (including zeroes). Results show that having worse peers during a DAEP placement has a significant negative effect on a student' adult earnings. Relative to peers in the Q1, having peers in Q5 (most disruptive) of peers' disruptiveness leads to 6.5 percent ($ 800) lower earnings at age 23-27.

[20] We utilize age 23 as the age for completion of higher education outcomes, and hence age-group 23-27 is the main focus for labor market outcomes. Nonetheless, we also show results for age group 18-22 and 18-27 in the appendix for both employment (figures A.7a and A.7b) and earnings (figures A.8a and A.8b.)

[21] Table 5, columns 1 and 2 show the impact corresponding to age group 18-22. Estimates show that for age 18-22, the impact is negative but not statistically significant. In this age group, individuals are in their early career years, likely to be enrolled in colleges. Hence, looking at only employment as a measure of productivity can be misleading. Therefore, to take this into account, we also look at a different measure of productivity i.e. activity rate. Activity measures the propensity to be either employed or enrolled in a college. Activity rate captures the productivity measure that is inclusive of involvement in any productive activity, and hence serves as a better measure of productivity during early adult years. Figure A.6a shows that moving students from Q1 to Q5 of peers' disruptiveness leads to significant decline in activity rate for students at age 18-22.

Age-Earnings Profile: To understand the trajectory of impact over time, we examine the impact on earnings for each age between 18-27. Figure presents the results from this analysis. The x-axis shows age at which impact on earnings is measured. The y-axis denotes age-specific earnings. Each point on the y-axis corresponding to a given age on the x-axis comes from a separate regression (equation 2) and shows impact for each quintile relative to Q1. There are two main takeaways from this analysis - 1) figure shows that as age increases, the accumulated penalty of having worse peers during school DAEP placement becomes larger i.e. the size of impact on earnings increases with age. This is in line with the literature that shows that initial labor market outcomes can have persistent long-term effects on individuals' later life earning trajectories (Gan, Shin and Li, 2010; Gregg, Tominey et al., 2004; Oreopoulos, Von Wachter and Heisz, 2012), and 2) the decline in earnings mainly shows up after age 22 i.e. the age at which one is likely to finish college and start working. Focusing on age 27, it corresponds to 8.5 percent ($ 1,272 for average earnings of $15,616) decline in average earnings. Given that we observed in figure that the magnitude of impact increases with age, we can use $1272 as a lower bound of impact on earnings beyond age 27 to calculate the net effect on lifetime earnings. Calculation shows that $1,272 loss in earnings per year (starting at age 27) amounts to a net loss of $33,484 in presented discounted value of lifetime earnings.[22]

Thus, these results show that exposure to disruptive peers in DAEPs during school can have significant long lasting negative impact on individuals employment, earning potentials, and economic well-being.

VI. Robustness Tests

Alternate Specifications.— We conduct a battery of robustness checks to test the validity of our results. Figure 11 summarizes the results from the first set of robustness tests. For reference, in row 1 (denoted by S0), we show our main estimates corresponding to all the main outcomes. Row 2-4 shows results from the robustness tests. For each specification, columns 1-2 shows

[22] PDV of lifetime income is given by, PDV = $P \times \frac{(1+g)^N - 1}{(1+g) - 1} \times \frac{1}{(1+\pi)^N}$ where, P = $1272, g = .01 , π = 0.0175, N= 75-27 = 48.

estimates corresponding to disciplinary outcomes, columns 3-5 for educational outcomes and columns 6-7 for labor market outcomes, denoted by the column header.

As a first test of robustness, we re-estimate the peer effects by including controls for peer characteristics such as race, gender, test scores, and reason for removal. Peer effects from this set of regression is outlined by the coefficient plot in row 2 (S1). Estimates show that the findings from this specification (S1) are qualitatively very similar to our findings from the main specification (S0), thus showing that we are not largely picking up the effects of peers' race, gender or say ability. In specification S2, we test the validity of our findings with inclusion of sending campus fixed effects. This is to take into account if there are any sending campus specific factors that may be driving the results. Again, we find that our estimates are fairly consistent with or without inclusion of this fixed effect.

Matching on peers.— In analysis so far, we have used students' assigned days of placement at DAEPs instead of actual placement duration to match with the relevant set of peers. We use do this primarily to avoid any endogeneity that may arise if peers disruptiveness influences a students' actual days of placement. However, while assigned days of placement is a cleaner variable, it can also lead to some measurement error in identifying the right set of peers. Hence, as a test for robustness, we re-match the peers based on students' actual days of placement and estimate the effects. Figure 11, specification S3 shows the estimates corresponding to this. Results from this specification are consistent with our previous findings (with slightly larger coefficients), and thus shows robustness of our main results.

Measure of peers' disruptiveness.— For our next robustness test, we use an alternative measure of peers' disruptiveness. Instead of counts of past suspension, here we use the number of days suspended in the past. Suspension days last range between 1-3 days and is highly correlated with the number of counts. We present findings from this alternate definition of peers' disruptiveness using days of suspension.[23] Figure 11 specification S4 shows the results corresponding to peers having 1 additional day of suspension per year in the past. While qualitatively the results the very similar, the coefficients are smaller than our baseline estimates. This is so because we are measuring the impact of 1 additional day of suspension instead of 1 additional count of

[23] While days can provide a more granular measure of past disciplinary action, there is also a lot of discretion across schools on how long they suspend a student for the same act. Hence, for these reasons, number of suspensions provide a more consistent measure.

suspension. Taking into consideration that 1 suspension count corresponds to 2.5 suspension days in our sample, the effect sizes then are fairly comparable to our baseline estimates.

Thus, we show that our findings are consistent and robust to a range of specifications and alternate definition of peers and disruptiveness.

Consistent sample.— In our main analysis, we imposed sample restrictions that allows us to retain maximum observations for each set of outcomes. For disciplinary outcomes we restricted sample to students who return to the Texas public education system sometime after the exit, for educational outcomes we restricted to individuals who are atleast 23 years old in the sample and for labor market outcomes, we restricted sample to individuals who are 27 years old in the sample. While this allows us to retain the maximum possible sample and provides power, it also makes it difficult to compare the estimates across the there set of outcomes. In addition, this can also affect the estimates if individuals in the older cohorts are more likely to be affected by peers' disruptiveness than younger cohorts even with time fixed effects. Hence, to get a more comparable estimate of the effects across all outcomes, we create a consistent sample that satisfies all three restrictions for the analysis. While this significantly reduces the sample size, this provides us a consistent sample across all set of outcomes and hence allows better comparability. Table 6 presents results from this sample, and shows that our findings are robust to even when we use the same sample for all outcomes.

Randomization Inference.— lastly, to argue that these results are meaningful and not spurious, we conduct a randomization inference by running 1000 regressions with placebo treatments for each outcome variable. For this, we create a placebo treatment variable by randomizing the peers' average yearly past suspensions for each student in the sample. Note that we keep the distribution of peers' disruptiveness same and simply randomize the assignment of it across students. We then estimate the peers effects for an additional 1000 times corresponding to each placebo assignment. We repeat this exercise for each outcome in the analysis. Figure 12 shows the result from this exercise. For each outcome on the x-axis, the range of all placebo coefficients is denoted by the confidence interval band, whereas the actual coefficient is given by the scatter plot. Figure shows that the actual estimated coefficient lies far away from the entire range of placebo betas and thus, provides evidence against having observed these coefficients just by chance.

VII. Peer Group Characteristics

So far in the paper, our main focus has been on understanding the impact of average peer disruptiveness on student's characteristics. In this section, we explore two additional characteristics of the peer group that may matter beyond the average peer disruptiveness.

Student-Peer Similarity. In the first exercise, we explore the role of social-distance in relation to the peer effects. For this, we create 2 dummy variables that captures whether or not the majority of peer group for a student is similar to the student in terms of 1) reason for removal and 2) in terms of race. To generate the dummy for similarity in reason for removal, we divide the reasons into two broad categories - a) more serious acts (drugs, sexual assault, fights) and b)less serious acts (violation of code of conduct, truancy). The dummy variable, $Dummy_{SimilarReason}$ = 1 if majority of peers (>50%) are removed for the same category of reason as the student, else 0. Similarly, we divide race of into two broad groups a) white and b) black, hispanic, others. $Dummy_{SimilarRace}$ = 1 if majority of peers (>50%) are of the same category of race as the student, else 0. We then interact the each dummy with the peers' disruptiveness in the main equation 1. Estimating equation in this case is given by:

$$\begin{aligned} Y_i = \lambda \times (\text{Peers' Avg Yearly Past Suspension}_i \times Dummy_i) + \zeta \times Dummy_i + \\ \beta \times \text{Peers' Avg Yearly Past Suspension}_i + \theta_{dy} + \gamma_{dl} + \alpha_t + \delta_r + X_{idy} + \epsilon_{idyt} \end{aligned} \tag{3}$$

where, coefficient λ measures the additional effect of having a peer group where a majority of peers share the same characteristic as the student, and D_i is the peer-group characteristic of interest.

Table 7 presents the coefficient λ from equation (3) corresponding to each dummy characteristic and each outcome of interest. Estimates show that when students are in a peer group where majority of peers are placed for the same reason category as the student, there is a larger impact of peers disruptiveness on students subsequent outcomes. Relative to students with non-similar peers, students with majority of peers sharing the same reason for removal are more likely to have higher subsequent removals, lower educational attainment, lower earnings. For similarity in race, while we do see a similar pattern, the coefficient are not statistically significant across all outcomes except for subsequent removals. Thus, the results show that social-distance of a student from his/her peer groups in terms of disruptive characteristic (reason for removal) can exacerbate the adverse effect of peers' disruptiveness on students' outcomes. This is in line with (Bayer, Hjalmarsson and Pozen, 2009) which shows that when inmates at detention centres are exposed to peers with a history of similar crime, it is likely to increase their crime-specific recidivism in the future.

Dispersion in Peers' Disruptiveness. As a second measure of peer-group characteristic, we look at the dispersion in peers' disruptiveness for each student. When there is lower dispersion in peers' disruptiveness in a peer group, it is more likely to create a consistent reinforcement.[24] To estimate this, we create a measure of dispersion in peers' disruptiveness. First, we generate the standard deviation (SD) of peers' disruptiveness for each student in the main sample. Figure A.11 shows the distribution of SD in peers' past suspension in the sample. Using this SD, we then generate a z-score for the SD in peers' disruptiveness to allow the interpretation of results in terms of 1-SD change. Using the z-score measure of dispersion,$Zi_{Dispersion}$, we estimate the interaction coefficient λ from the following equation:

$$\begin{aligned} Y_i = \lambda \times (\text{Peers' Avg Yearly Past Suspension}_i \times Zi_{Dispersion}) + \zeta \times Zi_{Dispersion} + \\ \beta \times \text{Peers' Avg Yearly Past Suspension}_i + \theta_{dy} + \gamma_{dl} + \alpha_t + \delta_r + X_{idy} + \epsilon_{idyt} \end{aligned} \tag{4}$$

where, coefficient λ measures the additional effect of having a peer group with larger dispersion in peers' disruptiveness, and $Zi_{Dispersion}$ is the z-score measure of dispersion in peers' disruptiveness. Results in Table 8 shows that for peers with similar average disruptiveness, having more concentrated peer group in terms of disruptiveness (i.e. smaller $Zi_{Dispersion}$) has a larger adverse impact on students' future outcomes compared to a more dispersed peer group (i.e. larger $Zi_{Dispersion}$). These results show that even for the same average disruptiveness, peer effects are likely to be stronger when there is a more consistent reinforcement through a less

[24] (Lee, Lee and Baek, 2021) shows that for two products with similar average rating, one with high variance is less informative of the quality or consumer satisfaction whereas the one with low variance in rating provides a more consistent message. Similar to this, when there are more peers with similar disruptiveness, students receive are influenced in a consistent way again and again, and hence the reinforcement of peer effects can be stronger compared to a scenario when they have more dispersed peers

dispersed peer group in terms of disruptiveness. Thus, these supplmentary results point to the importance of group characteristics beyond the average characteristics that can play important role in driving the peer effects.

VIII. Contextualization of Results

In this section, we compare our results to other studies and settings in the literature to provide a better interpretation and comparability of our findings.

First, we begin by comparing our findings on reinforcing peer effects. In context of detention centers, (Bayer, Hjalmarsson and Pozen, 2009) shows that increase in exposure to inmates with a history of same crime by 1 SD leads to increase in crime-specific recidivism by 10-20 percent. Similar to this, DAEPs mimic the detention type setting in the sense that it brings all the trouble makers under one roof which can lead to reinforcement of disruptive behavior among each other. We find that relative to Q1, having peers in Q5 of disruptiveness during the DAEP placement leads to 5-8 percent increase in future disciplinary recidivism or removal. While this is about half the size of reinforcing effects in (Bayer, Hjalmarsson and Pozen, 2009), it is also noteworthy that our results correspond to a relatively short duration of peer effects as compared to detention centers which are on average long term assignments, and hence show meaningfully large impact of disruptive peers at DAEPs.

Second, in terms of school-to-prison pipeline literature, a vast descriptive literature suggest that placement at DAEPs increases the chance of future incarceration for students placed at these schools. (Bacher-Hicks, Billings and Deming, 2019) who finds that exposure to districts with 1-SD higher propensity to suspend students leads to 0.38 additional suspensions per year for students. This in turn leads to 15-20 percent more likelihood of students to be arrested and incarcerated as adults. In comparison, we find that moving students from Q1 to Q5 of peers' disruptiveness leads to 0.13 more suspensions per year in the future. If we extrapolate our findings on additional suspension to the impact of suspension on incarcerations in (Bacher-Hicks, Billings and Deming, 2019), effect size of 0.13 additional suspensions from more disruptive peers would lead to 5-7 percent increase in the propensity of adult arrests and incarcerations. Thus, exposure to a group of more disruptive peers at DAEPs can have a significant impact in facilitating the school-to-prison pipeline.

To contextualize our results on earnings, we compare our findings with other papers on disruptive peer effects as well as literature on the effect of neighborhood. Carrell, Hoekstra and Kuka (2018) studies the effect of disruptive peers in a classroom and finds that exposure to one additional disruptive peer in class of 25 during elementary school reduces earnings at age 24-28 by 3 percent. Since all peers in our setting are disruptive peers, a direct comparison of our findings with these estimates is not possible. Instead, we think of our results as the intensive margin estimates of disruptive peers as we exploit the variation in peers' disruptiveness (measured by average yearly past suspensions) instead of the number of disruptive peers. We find that having peers with 1 additional yearly suspension in the past, results in 1.32 percent lower earnings at age 23-27, i.e. about half the size of effect from having 1 additional disruptive peer.

A broad and consistent literature finds that early childhood environments (neighborhood quality, class size, teacher quality, school quality, provision of medicare etc) play an important role determining the long-run outcomes of earnings of individuals. For example, (Chetty, Hendren and Katz, 2016) finds that children whose families take up an experimental voucher to move to a lower-poverty area when they are less than 13 years old have an annual income that is \$3,477 (31 percent) higher on average relative to a mean of \$11,270 in the control group in their mid-twenties. In comparison, we find that students who have peers in Q5 of disruptiveness disrtibution (most disruptive) have 6.5 percent ($\sim$ \$800) lower average earnings relative to those with peers in Q1 at age 23-27. This is approximately one-fifth the size of impact from moving to a better neighborhood in early childhood. However, there are few caveats to keep in mind while comparing these results - a) unlike (Chetty, Hendren and Katz, 2016) which has a pure non-treated group (those who do not move to better neighborhoods), all students in our setting interact with disruptive peers and hence, there is no pure control group. Therefore, our results on students' outcomes show relative differences in effects for more treated versus less treated students. Hence, our findings can be thought of as a lower bound to pure treatment effects if there existed a peer group with no disruptive history. b) the results in our setting comes from a short term peer effects whereas (Chetty, Hendren and Katz, 2016) shows impacts of a sustained exposure to a better neighborhood on adult earnings. In this regard, our results may seem large to be driven by a short term peer effects. However, it is important to note that our sample corresponds to student population who are among the most disruptive and problematic group of student population, and hence, we expect the adverse effects to be large for this group. In terms of some other literature on peers and neighborhood, our estimates on earnings (decline of 6.5 percent at age 23-27) is about one-third the effect on wages from a 5-year exposure to school desegregation among blacks (leading to about 15 percent increase in adult wages) (Johnson, 2011); and one-third from demolition of public housing in Chicago (16 percent effects on adult wages) (Chyn, 2018).

Thus, these comparisons show that disruptive peer effects at DAEPs has a significant and meaningfully large size of impact on students' short and long-run outcomes.

IX. Discussion and Conclusion

Schools across the nation use disciplinary removal of students to DAEPs as a way to impart positive behavior among disruptive students and provide effective learning in regular schools. In this paper, we show evidence on reinforcing peer effects that arise when students are removed from their regular setting and placed at the DAEPs. This exposes students to a concentrated group of disruptive students. Our findings show that having peers with higher average disruptiveness during a students' DAEP placement, leads to higher future disciplinary removals for the students, lowers their school and college education outcomes, and decreases their employment and earning potentials. So, what does these results say in terms of policy implications?

The policy discussion related to peer effects is a fairly complex topic. Peer effects is a natural part of any group setting and hence, eliminating peer effects is not straightforward. However, if peer effects at DAEPs exacerbates disruptive behavior among students instead of reducing it, a natural question that arises is if reducing DAEP placements is the first place can be help? While our paper shows the adverse impact of peers at DAEPs, these effects are conditional on student being placement at a DAEP. Hence, whether or not reducing DAEP placements can help mitigate the adverse impacts of peers at DAEPs, is still an empirical question. This requires understanding of full implications of DAEP placement - a) impact of a student's DAEP placement on their own outcomes, impact of a student's DAEP placement on outcomes of regular students, and impact of a student's DAEP placement on outcomes of other students placed at the DAEP (this paper). Regardless, our paper informs us of an important channel through which DAEP placements can lead to worse future outcomes among students.

In past decade, there has also been a push for early intervention and positive reinforcement programs. Given that minorities and disadvantaged students are disproportionately represented in the DAEP population, early intervention with a focus on prevention; teamwork between teachers and parents; understanding students' needs by case to case basis; and building a positive school climate, can help reduce the intensity of the problem. This can help in reducing the probability of student being sent to a DAEP and thus, avoid the disruptive peer effects at DAEPs, as well as reduce the negative effects on regular students.

Past literature has shown the disruptive peers have a negative impact on regular students. As a result, schools have used student removal as a way to separate disruptive students from regular students and ensure effective learning for both groups of students. However, our paper presents new evidence which highlights that adverse impact of peer at DAEPs when a disruptive student is placed at these schools. Thus, if the aim of DAEPs is to a provide separate setting to improve the outcomes of disruptive students, we need to take into account the negative impact of disruptive peer at DAEPs that stems from putting all disruptive students under one roof. These results highlights the need to investigate factors that can mititgate the adverse impact of peers at DAEPs and prevent students from falling off the school system.

References

Appleseed. 2007. "Texas' School-to-Prison Pipeline: Dropout to Incarceration."

Appleseed. 2018. "Texas: The State of School Discipline."

Aron, Laudan Y, and Janine M Zweig. 2003. "Educational Alternatives for Vulnerable Youth: Student Needs, Program Types, and Research Directions." *Urban Institute (NJ1)*.

Bacher-Hicks, Andrew, Stephen B Billings, and David J Deming. 2019. "The school to prison pipeline: Long-run impacts of school suspensions on adult crime." National Bureau of Economic Research.

Bayer, Patrick, Randi Hjalmarsson, and David Pozen. 2009. "Building criminal capital behind bars: Peer effects in juvenile corrections." *The Quarterly Journal of Economics*, 124(1): 105–147.

Becker, Gary S. 1996. *Accounting for tastes.* Harvard University Press.

Bifulco, Robert, Jason M Fletcher, and Stephen L Ross. 2011. "The effect of classmate characteristics on post-secondary outcomes: Evidence from the Add Health." *American Economic Journal: Economic Policy*, 3(1): 25–53.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes. 2013. "Under pressure? The effect of peers on outcomes of young adults." *Journal of Labor Economics*, 31(1): 119–153.

Carrell, Scott E, and Mark L Hoekstra. 2010. "Externalities in the classroom: How children exposed to domestic violence affect everyone's kids." *American Economic Journal: Applied Economics*, 2(1): 211–28.

Carrell, Scott E, Mark Hoekstra, and Elira Kuka. 2018. "The long-run effects of disruptive peers." *American Economic Review*, 108(11): 3377–3415.

Chetty, Raj, John N Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan. 2011. "How does your kindergarten classroom affect your earnings? Evidence from Project STAR." *The Quarterly journal of economics*, 126(4): 1593–1660.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment." *American Economic Review*, 106(4): 855–902.

Chyn, Eric. 2018. "Moved to opportunity: The long-run effects of public housing demolition on children." *American Economic Review*, 108(10): 3028–56.

Dahl, Gordon B, Katrine V Løken, and Magne Mogstad. 2014. "Peer effects in program participation." *American Economic Review*, 104(7): 2049–74.

Dearden, Lorraine, Javier Ferri, and Costas Meghir. 2002. "The effect of school quality on educational attainment and wages." *Review of Economics and Statistics*, 84(1): 1–20.

Denning, Jeffrey T, Richard Murphy, and Felix Weinhardt. 2020. "Class rank and long-run outcomes." National Bureau of Economic Research.

Dishion, Thomas J, Joan McCord, and Francois Poulin. 1999. "When interventions harm: Peer groups and problem behavior." *American psychologist*, 54(9): 755.

Duflo, Esther, and Emmanuel Saez. 2003. "The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment." *The Quarterly journal of economics*, 118(3): 815–842.

Durlauf, Steven N, et al. 1997. *The memberships theory of inequality: ideas and implications.* Social Systems Research Institute, University of Wisconsin.

Fabelo, Tony, Michael D Thompson, Martha Plotkin, Dottie Carmichael, Miner P Marchbanks, and Eric A Booth. 2011. "Breaking schools' rules: A statewide study of how school discipline relates to students' success and juvenile justice involvement." *New York: Council of State Governments Justice Center*.

Field, Erica, Seema Jayachandran, Rohini Pande, and Natalia Rigol. 2016. "Friendship at work: Can peer effects catalyze female entrepreneurship?" *American Economic Journal: Economic Policy*, 8(2): 125–53.

Gan, Li, Jaeun Shin, and Qi Li. 2010. "Initial Wage, Human Capital and Post Wage Differentials." *Hitotsubashi Journal of Economics*, 79–97.

Gaviria, Alejandro, and Steven Raphael. 2001. "School-based peer effects and juvenile behavior." *Review of Economics and Statistics*, 83(2): 257–268.

Gould, Eric D, Victor Lavy, and M Daniele Paserman. 2009. "Does immigration affect the long-term educational outcomes of natives? Quasi-experimental evidence." *The Economic Journal*, 119(540): 1243–1269.

Gregg, Paul, Emma Tominey, et al. 2004. "The wage scar from youth unemployment."

Guryan, Jonathan, Kory Kroft, and Matthew J Notowidigdo. 2009. "Peer effects in the workplace: Evidence from random groupings in professional golf tournaments." *American Economic Journal: Applied Economics*, 1(4): 34–68.

Hoxby, Caroline M. 2000. "Peer effects in the classroom: Learning from gender and race variation."

Johnson, Rucker C. 2011. "Long-run impacts of school desegregation & school quality on adult attainments." National Bureau of Economic Research.

Kleiner, Brian, Rebecca Porch, Elizabeth Farris, and Bernard Greene. 2002. "Public alternative schools and programs for students at risk of education failure: 2000-01." *Education Statistics Quarterly*, 4(3): 42–47.

Lavy, Victor, and Analia Schlosser. 2011. "Mechanisms and impacts of gender peer effects at school." *American Economic Journal: Applied Economics*, 3(2): 1–33.

Lavy, Victor, Olmo Silva, and Felix Weinhardt. 2012. "The good, the bad, and the average: Evidence on ability peer effects in schools." *Journal of Labor Economics*, 30(2): 367–414.

Lee, Soyeon, Saerom Lee, and Hyunmi Baek. 2021. "Does the dispersion of online review ratings affect review helpfulness?" *Computers in Human Behavior*, 117: 106670.

Levey, Emma KV, Claire F Garandeau, Wim Meeus, and Susan Branje. 2019. "The longitudinal role of self-concept clarity and best friend delinquency in adolescent delinquent behavior." *Journal of youth and adolescence*, 48(6): 1068–1081.

Manski, Charles F. 1993. "Identification of endogenous social effects: The reflection problem." *The review of economic studies*, 60(3): 531–542.

Marchbanks III, Miner P, Jamilia J Blake, Danielle Smith, Allison L Seibert, Dottie Carmichael, Eric A Booth, and Tony Fabelo. 2014. "More than a drop in the bucket: The social and economic costs of dropouts and grade retentions associated with exclusionary discipline." *Journal of Applied Research on Children: Informing Policy for Children at Risk*, 5(2): 17.

Marchbanks III, Miner P, Jamilia J Blake, Eric A Booth, Dottie Carmichael, Allison L Seibert, and Tony Fabelo. 2015. "The economic effects of exclusionary discipline on grade retention and high school dropout." *Closing the school discipline gap: Equitable remedies for excessive exclusion*, 59–74.

Murphy, Richard, and Felix Weinhardt. 2020. "Top of the class: The importance of ordinal rank." *The Review of Economic Studies*, 87(6): 2777–2826.

NYT. 2014. "Where We Came From and Where We Went, State by State."

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz. 2012. "The short-and long-term career effects of graduating in a recession." *American Economic Journal: Applied Economics*, 4(1): 1–29.

Rosaz, Julie, Robert Slonim, and Marie Claire Villeval. 2016. "Quitting and peer effects at work." *Labour Economics*, 39: 55–67.

Rumberger, Russell W, and Daniel J Losen. 2017. "The Hidden Costs of California's Harsh School Discipline: And the Localized Economic Benefits from Suspending Fewer High School Students." *Civil Rights Project-Proyecto Derechos Civiles*.

Sacerdote, Bruce. 2001. "Peer effects with random assignment: Results for Dartmouth roommates." *The Quarterly journal of economics*, 116(2): 681–704.

Van Acker, Richard. 2007. "Antisocial, aggressive, and violent behavior in children and adolescents within alternative education settings: Prevention and intervention." *Preventing School Failure: Alternative Education for Children and Youth*, 51(2): 5–12.

Vigdor, Jacob, and Thomas Nechyba. 2007. "Peer effects in North Carolina public schools." *Schools and the equal opportunity problem*, 73–101.

Weisburst, Emily K. 2019. "Patrolling public schools: The impact of funding for school police on student discipline and long-term education outcomes." *Journal of Policy Analysis and Management*, 38(2): 338–365.

List of Tables

List of Figures

Main Tables and Figures

Table 1: SUMMARY STATISTICS

High School	(1) Student DAEP	(2) Average Peer DAEP	(3) Average Texas
Demographic and Academic Variables			
Age (yrs)	15.79	15.83	15.694
Female (%)	32.0	25.01	48.6
White (%)	21.6	17.9	29.0
Black (%)	21.9	25.2	13.7
Hispanic (%)	54.1	54.7	51.2
Economically Disadvantaged (%)	62.5	66.6	61.3
Special Education (%)	9.6	18.4	10.5
Past Math Score (zscore)	-0.479	-0.652	-1.043
Total Past Suspensions (#)	9.374	17.04	1.93
Outcome Variables			
Future suspensions per year (#)	2.58		
Future DAEP placement per year (#)	0.48		
High School Graduation (%)	50		
College Enrollment (%)	34		
College Graduation (%)	7		
Annual Qtrs Employed at 23-27 (#)	1.93		
Annual Earnings at 23-27 (USD)	10,000.8		
N	162,654		

Notes: Table 1 shows the summary statistics (average value) for demographic, academic, and disciplinary characteristics for the main student sample in DAEPs (column 1), their average peers in the DAEP (column 2), and for all students in the Texas (column 3). In addition, for main student sample, column 1 also shows the average value corresponding to main outcomes of interest. *Sample:* High school students placed at DAEPs between 2004-2018 *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Table 2: BALANCE TEST

	(1) Past Suspensions	(2) Assign days	(3) Difference Assign-Actual	(4) White	(5) Black	(6) Hispanic	(7) Eco Disadv	(8) Special Educ	(9) LEP	(10) Past Score
Sample: High School										
Peers' Past Suspension counts	-0.0174	-0.0437	-0.0102	-0.0017	0.0011	0.0006	0.0014	0.0012	0.0003	-0.0019
	(0.0155)	(0.0271)	(0.0277)	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0007)	(0.0008)	(0.0016)
Mean	2.80	4.42	32.31	0.22	0.22	0.54	0.63	0.10	0.11	-0.48
Obs	161828	161828	161828	161828	161828	161828	161828	161828	161828	161828

Notes: Table 2 shows the results from the balance test. Each column shows the impact of peers' disruptiveness (proxied by peers' average yearly past suspension counts) on students' pre-determined demographic, academic, and disciplinary characteristics. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, and DAEP $\times$ duration-bin FEs. Standard errors are clustered at the DAEP level. *Sample:* High schools students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01.

Table 3: MAIN RESULT I: IMPACT ON FUTURE DISCIPLINARY OUTCOMES

	(1) # of Future Suspensions per year	(2) # of Future DAEP placements Per Year	(3) # of Future Suspensions per year (>0)	(4) # of Future DAEP Placement per year (>0)
Sample: High School				
Peer's Past Suspensions Counts	0.0168*	0.0110**	0.0182**	0.0236*
	(0.010)	(0.005)	(0.009)	(0.012)
Mean of Dep Var	2.58	0.48	3.20	1.29
Observations	138826	138826	89629	51578

Notes: Table shows the effect of peers' disruptiveness (proxied by peers' average yearly past suspension counts) on student's subsequent disciplinary outcomes - future suspensions per year and future DAEP placements per year. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and return to the Texas public schools after their DAEP exit by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 4: MAIN RESULT II: IMPACT ON FUTURE EDUCATIONAL OUTCOME

	(1) High-School Graduation	(2) College Readiness	(3) College Enrollment	(4) College Graduation
Sample: High School				
Peer's Past Suspension Counts	-0.0031**	-0.0022**	-0.0028*	-0.0016*
	(0.002)	(0.001)	(0.002)	(0.001)
Mean of Dep Var	0.50	0.12	0.34	0.07
Observations	90890	90908	90908	90908

Notes: Table shows the effect of peers' disruptiveness (proxied by peers' average yearly past suspension counts) on student's subsequent educational attainment - high school graduation, college readiness indicator(based on a statewide test), college enrollment, and college graduation. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast 23 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01.

Table 5: MAIN RESULT III: IMPACT ON FUTURE PRODUCTIVITY AND LABOR OUTCOME

	Age Bracket: 18-22 years		Age bracket: 23-27 years	
	Employment Qtrs Per Year (1)	Annual Earnings ((USD) (2)	Employment Qtrs Per Year (3)	Annual Earnings ((USD) (4)
Sample: High School				
Peer's Past Suspension counts	-0.0146	-73.0773**	-0.0592*	-224.8178***
	(0.023)	(31.332)	(0.033)	(74.913)
Mean of Dep Var	9.23	7035.79	9.97	13225.48
Observations	101290	101290	43230	43230

Notes: Table shows the effect of peers' disruptiveness (proxied by peers' average yearly past suspension counts) on student's subsequent labor-market outcomes - average quarters of employment and average annual earnings. Columns 1-2 shows outcomes at age 18-22, whereas columns 3-4 shows outcomes at age 23-27. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. Columns 1-2 restricts sample to those atleast 23 years in age by 2019, whereas columns 3-4 restricts it to 27 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01.

Table 6: ROBUSTNESS TEST: CONSISTENT LONG-RUN SAMPLE

	# of Future Suspensions per Year	# of Future DAEP removal per Year	High-School Graduation	College Readiness	College Enrollment	College Graduation	Activity Per Year (Educ/Emp)	Employment Quarters Total, all Years	Wages Per Year (USD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample: High School									
Peer's Past Suspensions Counts	0.001	0.005*	-0.002***	-0.003**	-0.003***	-0.001	-0.002***	-0.043***	-74.025***
	(0.008)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.014)	(17.605)
Mean of Dep Var	2.05	0.50	0.11	0.51	0.33	0.06	0.69	9.64	7318.34
Observations	88206	88206	88206	88206	88206	88206	88206	88206	88206

Notes: Table shows the effect of peers' disruptiveness (proxied by peers' average yearly past suspension counts) on student's subsequent disciplinary outcomes (columns 1-2), educational attainment (columns 3-6), and labor-market outcomes at age 18-22 (columns 7-8) corresponding to a sample that is consistent across all outcomes. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018, who ever return to public schools after exit from the DAEP and are atleast 23 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 7: IMPACT BY STUDENT-PEER SIMILARITY

	# of Future Suspensions per Year (1)	# of Future DAEP removal per Year (2)	High-School Graduation (3)	College Enrollment (4)	College Graduation (5)	Activity Per Year (age 18-22) (6)	Employment Quarters (age 18-22) (7)	Earnings Per Year (age 18-22) (8)
Peer's Past Susp× Similar Reason	0.0350**	0.0062	-0.0067***	-0.0030	-0.0018**	-0.0026*	-0.0610**	-60.7026*
	(0.018)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.027)	(35.701)
Observations	123174	123174	101290	101290	101290	101290	101290	101290
Peer's Past Susp × Similar Race	0.0629***	0.0235***	0.0034	0.0029	-0.0009	0.0004	-0.0002	-63.9587
	(0.015)	(0.007)	(0.002)	(0.003)	(0.001)	(0.002)	(0.039)	(44.941)
Observations	123174	123174	101290	101290	101290	101290	101290	101290

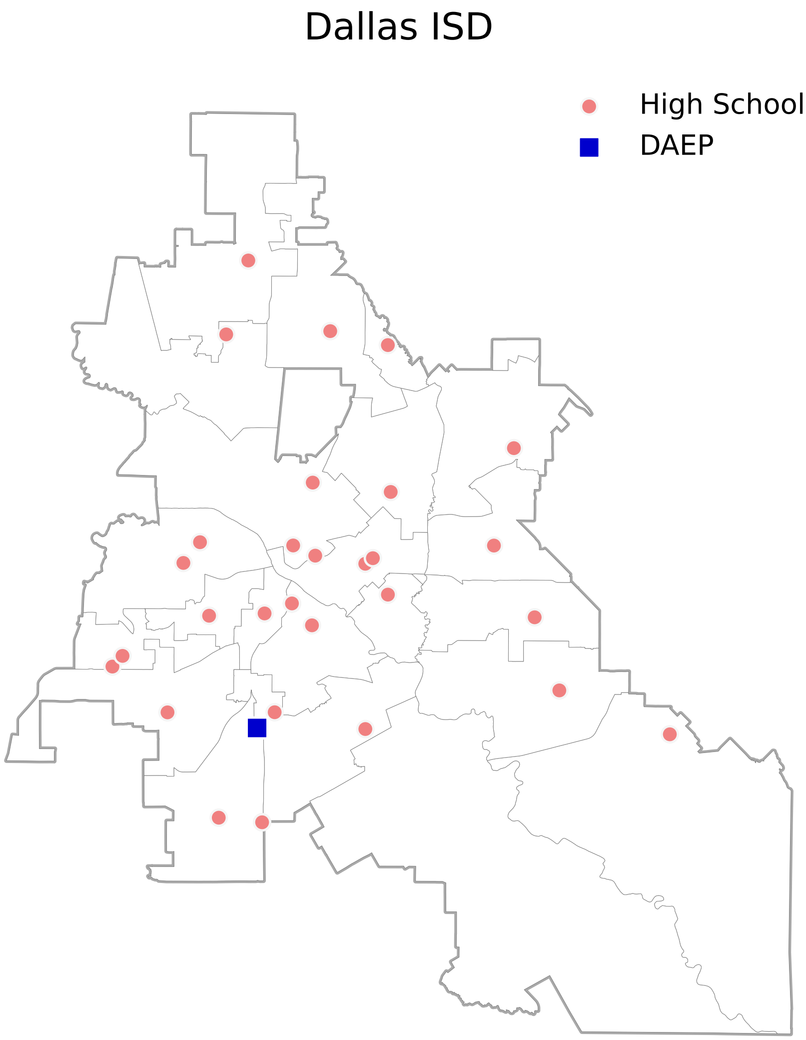
Notes: Table shows the effect of interaction effect of a dummy for peer-group similarity with peers' disruptiveness (i.e. coefficient λ from equation 3) on student's subsequent disciplinary outcomes (columns 1-2), educational attainment (columns 3-6), and labor-market outcomes at age 18-22 (columns 7-8). In top panel, $Dummy_{SimilarReason}$ = 1 if majority of peers (>50%) are removed for the same category of reason as the student, else 0. Similarly, in bottom panel, $Dummy_{SimilarRace}$ = 1 if majority of peers (>50%) are of the same category of race as the student, else 0. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. Columns 1 and 2 further restricts sample to students who ever return to public schools after exit from the DAEP, and columns 3-8 to those who are atleast 23 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8: IMPACT BY DISPERSION IN PEERS' DISRUPTIVENESS

	(1) # of Future Suspensions per Year	(2) # of Future DAEP removal per Year	(3) High-School Graduation	(4) College Enrollment	(5) College Graduation	(6) Activity Per Year (age 18-22)	(7) Employment Quarters (age 18-22)	(8) Earnings Per Year (age 18-22)
Peer's Past Susp × Z-Dispersion	-0.0088*	0.0014	0.0022***	0.0012	0.0007*	-0.0005	-0.0232**	-19.1338
	(0.005)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.010)	(13.797)
Observations	123174	123174	101290	101290	101290	101290	101290	101290

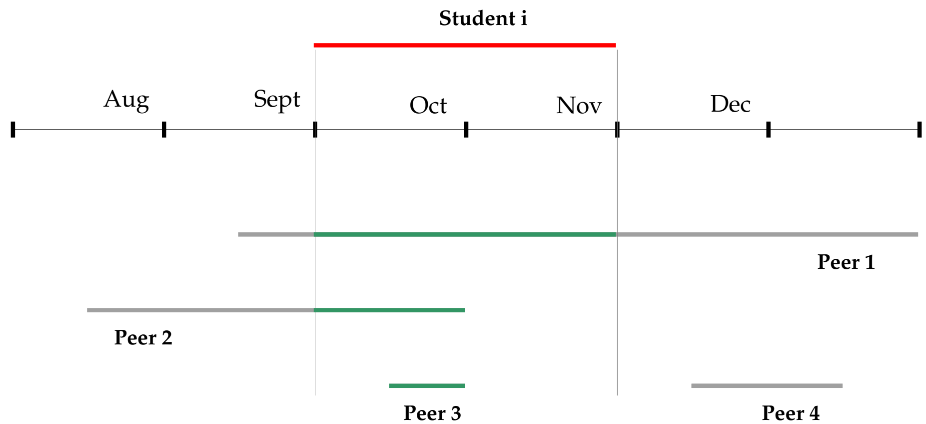
Notes: Table shows the effect of interaction effect of dispersion in peer-group disruptiveness with peers' average disruptiveness (i.e. coefficient λ from equation 4) on student's subsequent disciplinary outcomes (columns 1-2), educational attainment (columns 3-6), and labor-market outcomes at age 18-22 (columns 7-8). $Z_{Dispersion}$ denotes the z-score of standard deviation in peers' disruptiveness at the student level. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. Columns 1 and 2 further restricts sample to students who ever return to public schools after exit from the DAEP, and columns 3-8 to those who are atleast 23 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01.

Figure 1: Map of Dallas Independent School District



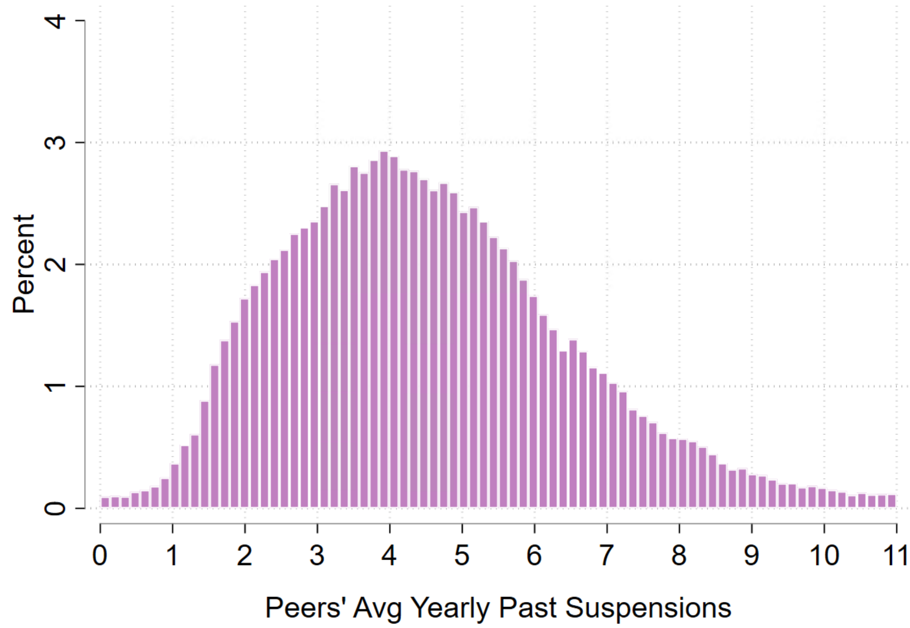
Notes: Figure shows the map of Dallas Independent School District. Orange circles show all the regular high schools and whereas the blue square represents the DAEP for high school students. While the ratio may vary across different districts, figure illustrate that a large number of regular schools send their students to any given DAEP within a district.

Figure 2: MATCHING STUDENT WITH RELEVANT PEERS

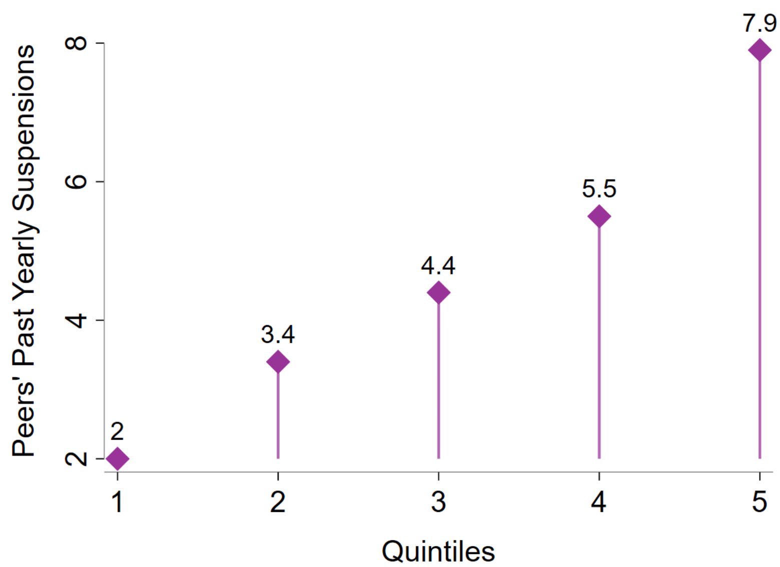


Notes: Figure shows a hypothetical example to illustrate that for any student i who placed at a DAEP for the first time, their peers are determined by the degree of overlap with each peer placed at the same DAEP during the student's placement duration. Student i's placement duration is denoted by the red line, whereas each peer's placement duration by the gray line. Green line shows the overlap between student i's and peers' placement duration. In this example, for student i, the relevant peers are peer 1, peer 2, and peer 3 only. Even though peer 4 is placed at the same DAEP in the same academic year, there is no overlap between student i's and peer 4's placement duration. Hence, peer 4 is not counted towards student i's peers.

Figure 3: Distribution of Peers' Disruptiveness



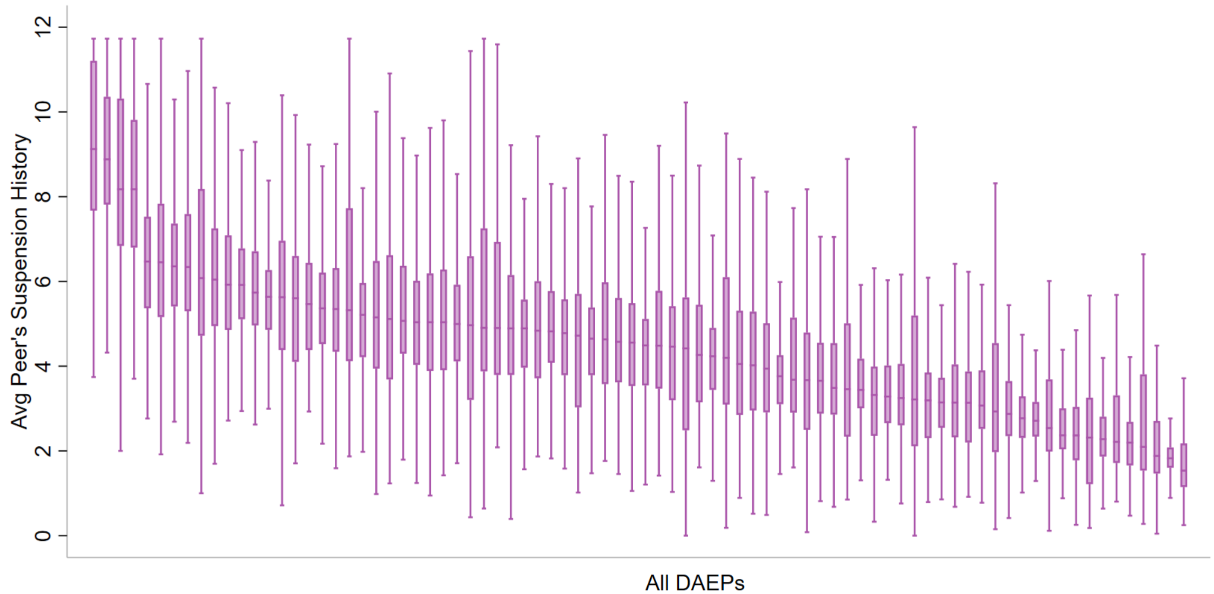
(a) Distribution of Average Peer Distuptiveness



(b) Average of Peers' Distuptiveness, by Quintiles

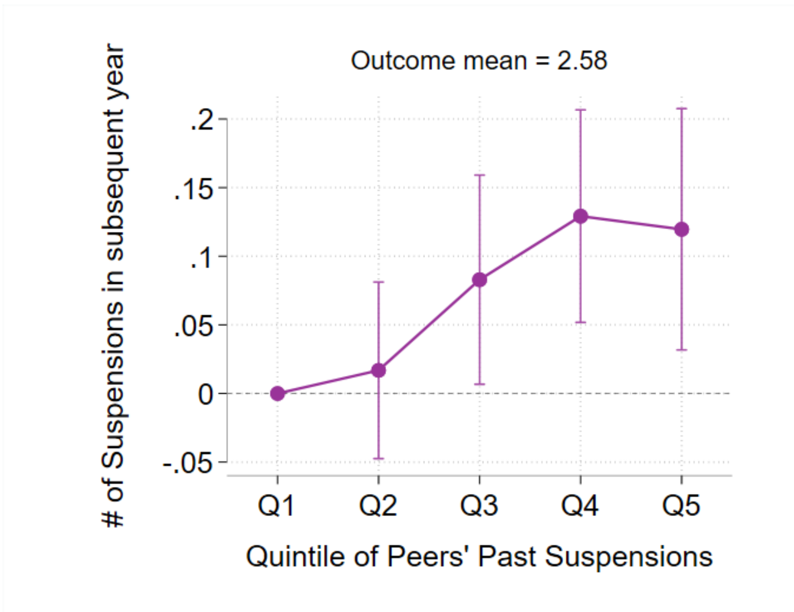
Notes: Figure shows the distribution of peers' average disruptiveness (proxied by their average yearly past suspension counts) for students in the main sample. Figure 3a shows distribution for continuous measure of peer disruptiveness whereas figure 3b shows average of peers' disruptiveness for each quintile of the distribution. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 4: Within DAEP Variation in Peers' Disruptiveness

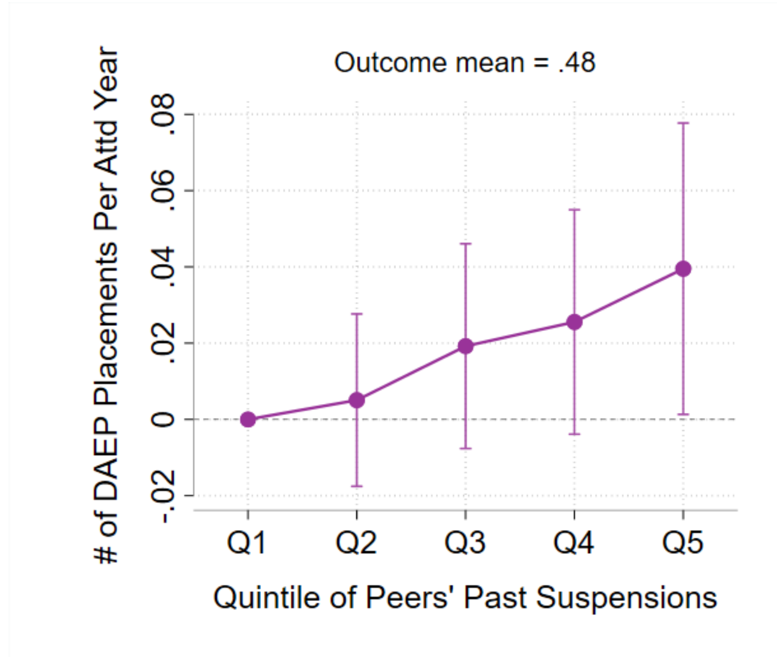


Notes: Figure shows the variation in peers' disruptiveness within DAEPs as well as across DAEPs, over time. Each bar on the x-axis corresponds to one particular DAEP, whereas y-axis denotes peers' disruptiveness for students in the main analysis sample. For each DAEP on x-axis, figure shows the box-plot of variation in peers' disruptiveness over time, where the DAEPs are sorted in descending order of their average peer disruptiveness. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 5: IMPACT OF SUBSEQUENT DISCIPLINARY OUTCOMES



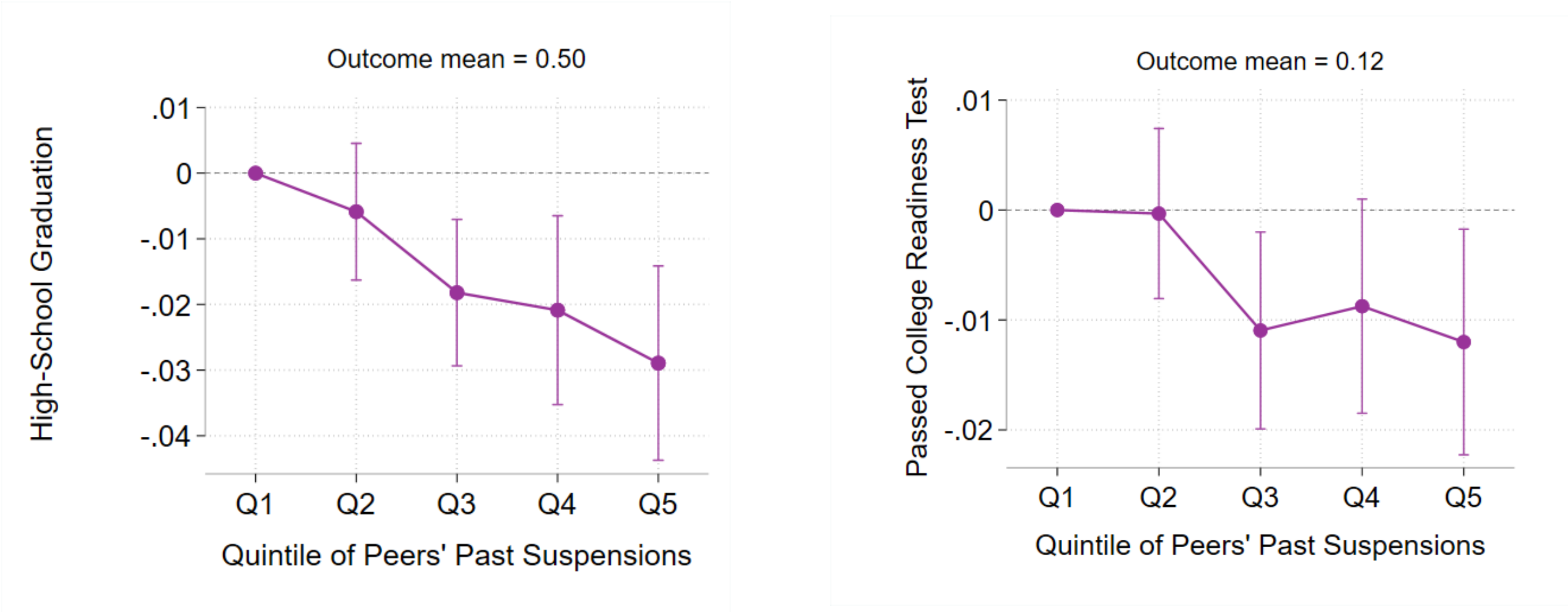
(a) SUSPENSIONS



(b) DAEP PLACEMENTS

Notes: Figure shows the impact of peers' disruptiveness on students' subsequent disciplinary outcomes. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes students' future removals. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. 5a plots the impact on students' future suspensions per year, whereas 5b shows impact on future DAEP placements per year. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and who return to public schools after their DAEP exit. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 6: Impact of End of School Outcomes

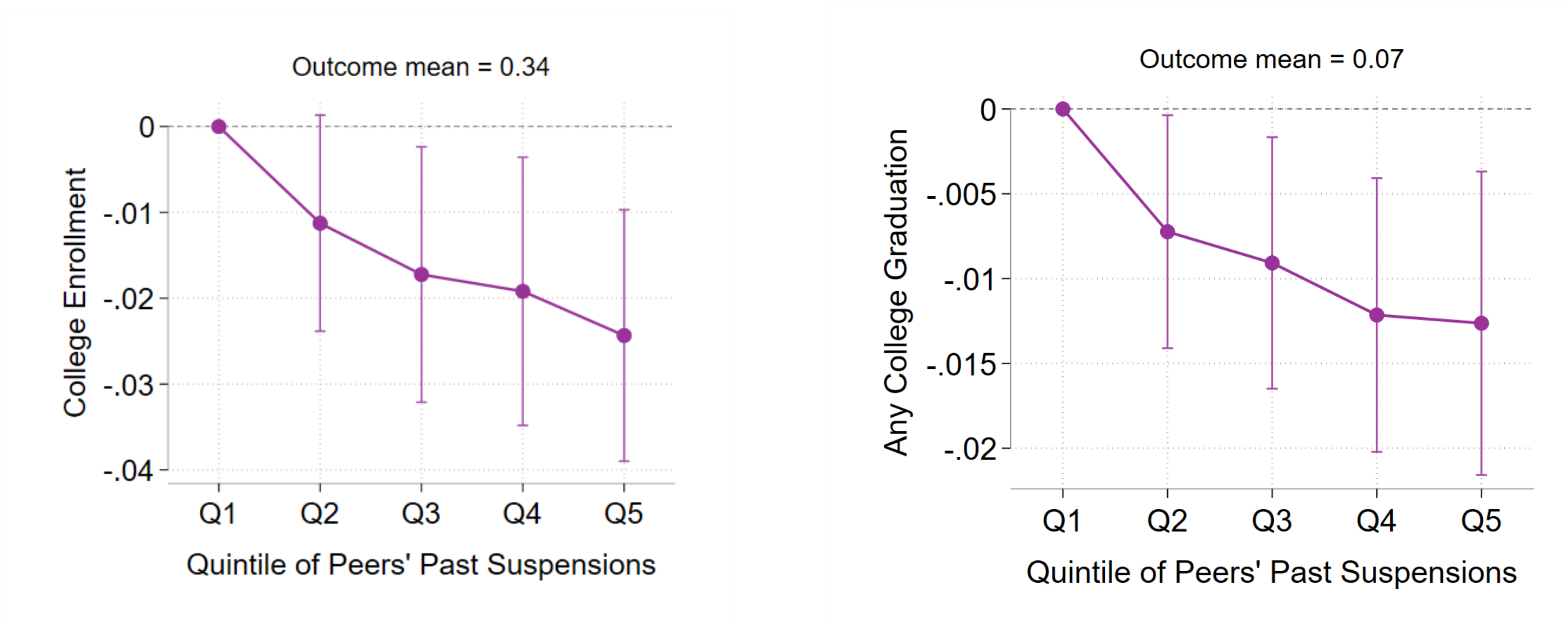


(a) High School Graduation

(b) Measure of College Readiness

Notes: Figure shows the impact of peers' disruptiveness on students' high school educational outcomes. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' end of school outcomes. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. 6a plots the impact on students' high school graduation, whereas 6b shows impact on their college readiness (a pass/fail indicator based on statewide test - Texas Success Initiative Assessment (TSIA) to determine a student's readiness for college-level coursework in the general areas of reading, writing, and mathematics.). All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast of age 23 by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 7: IMPACT OF COLLEGE OUTCOMES

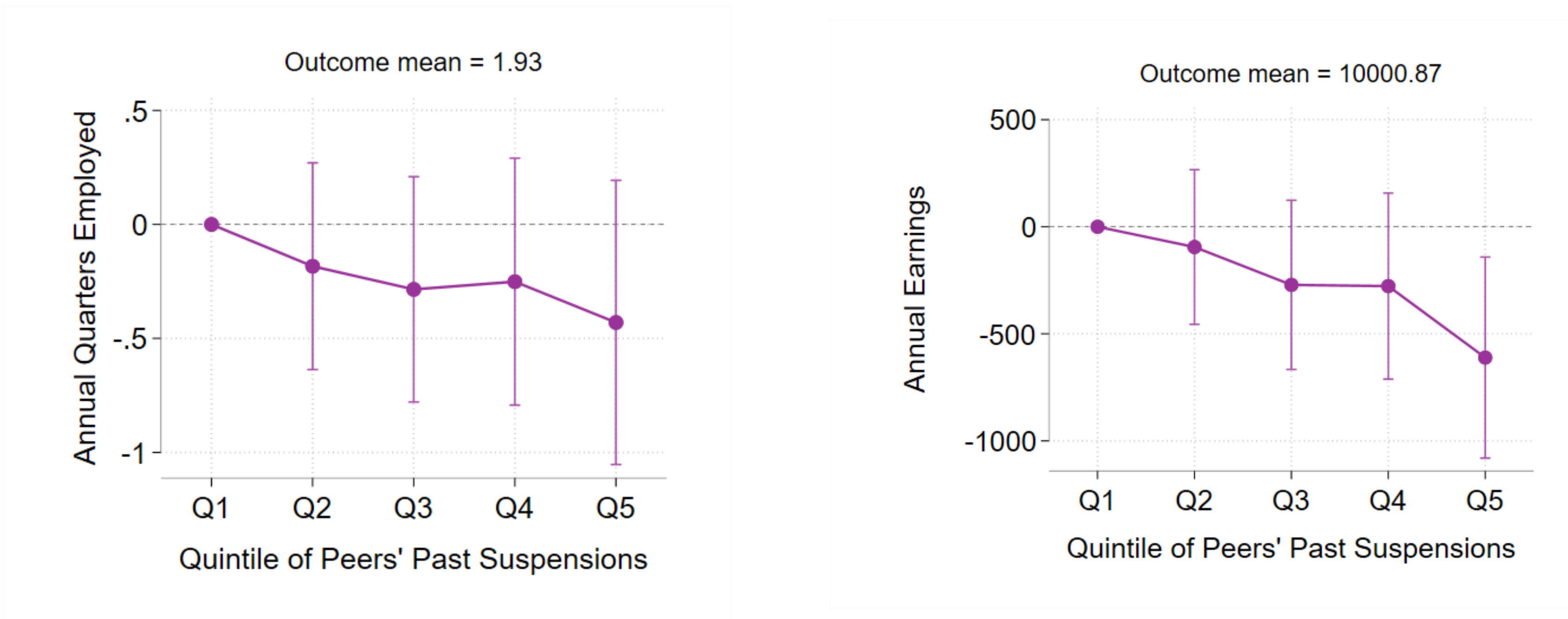


(a) COLLEGE ENROLLMENT

(b) COLLEGE GRADUATION

Notes: Figure shows the impact of peers' disruptiveness on students' higher educational attainment. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' college outcomes. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. 7a plots the impact on students' college enrollment, whereas 7b shows impact on their college graduation. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast of age 23 by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 8: IMPACT OF LABOR MARKET OUTCOMES

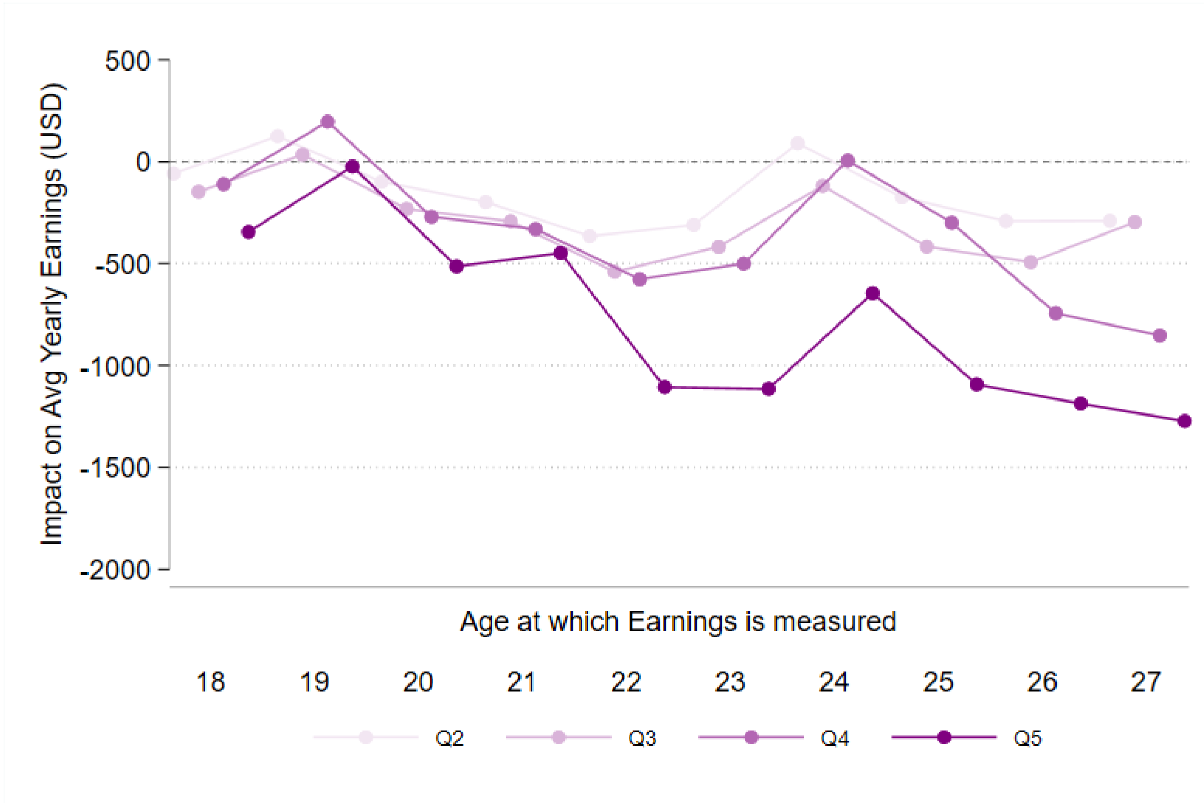


(a) ANNUAL QUARTERS OF EMPLOYMENT

(b) AVERAGE ANNUAL EARNINGS

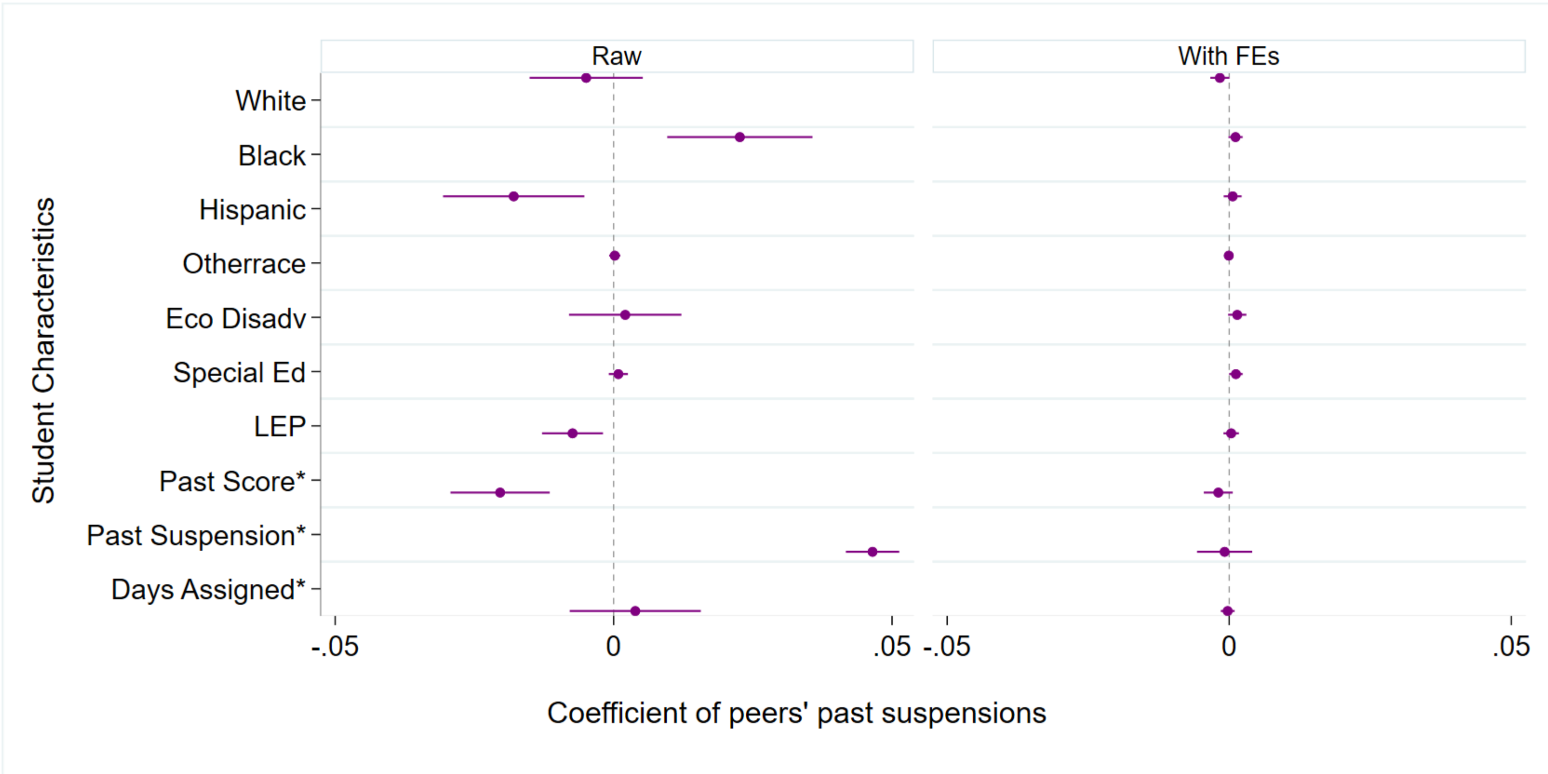
Notes: Figure shows the impact of peers' disruptiveness on students' long-run labor market outcomes. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' end of school outcomes. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. 8a plots the impact on the average annual quarters of employment at age 23-27, whereas 8b shows impact on average annual earnings at age 23-27. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast of age 27 by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 9: IMPACT ON AVERAGE ANNUAL WAGE AT EACH AGE GROUP BETWEEN 18-27 — QUINTILE ANALYSIS



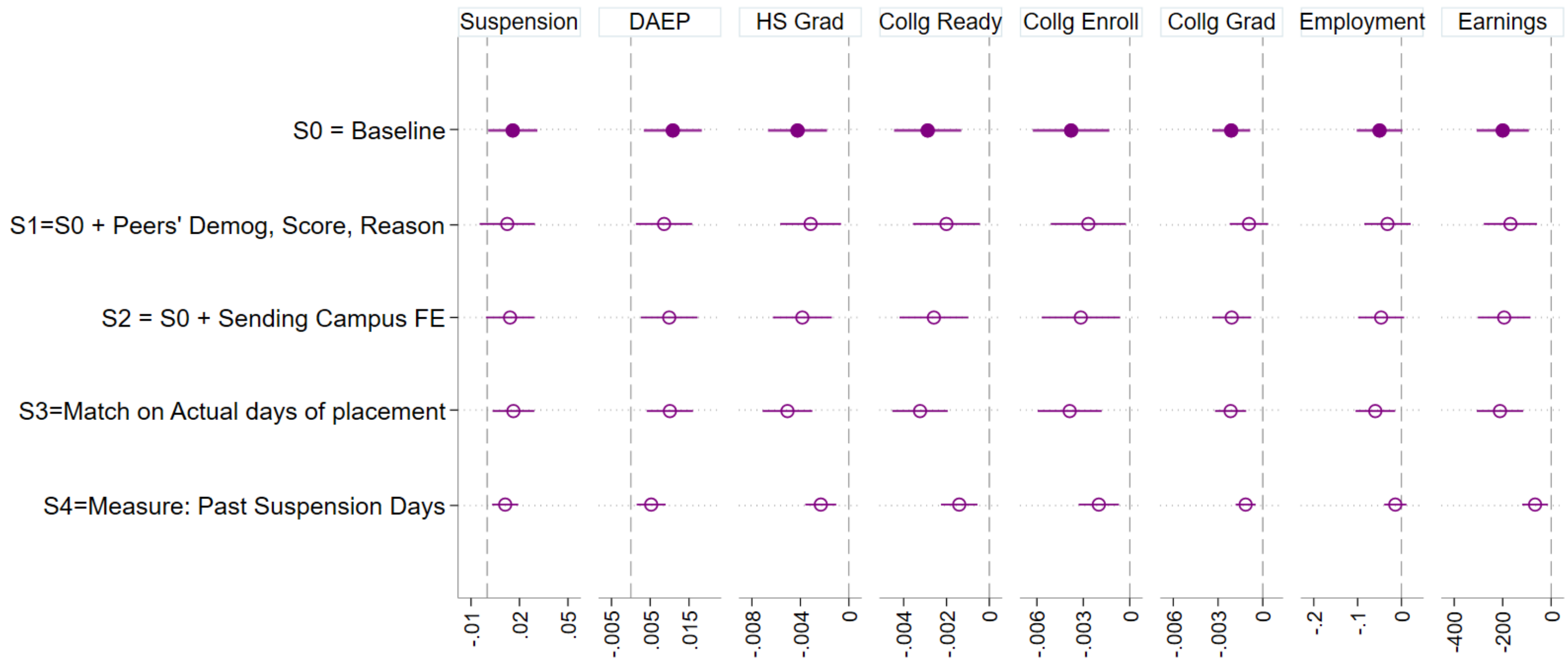
Notes: Figure plots the impact of peers' disruptiveness on students' earnings at each age between 18-27. The x-axis shows age at which earnings is measured. The y-axis denotes age-specific earnings. Each point on the y-axis corresponding to a given age on the x-axis comes from a separate regression (equation 2). For each age, figure shows the impact for each quintile of peers' disruptiveness relative to Q1 (omitted). All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 10: BALANCE BETWEEN PEERS' DISRUPTIVENESS AND STUDENTS' CHARACTERISTICS



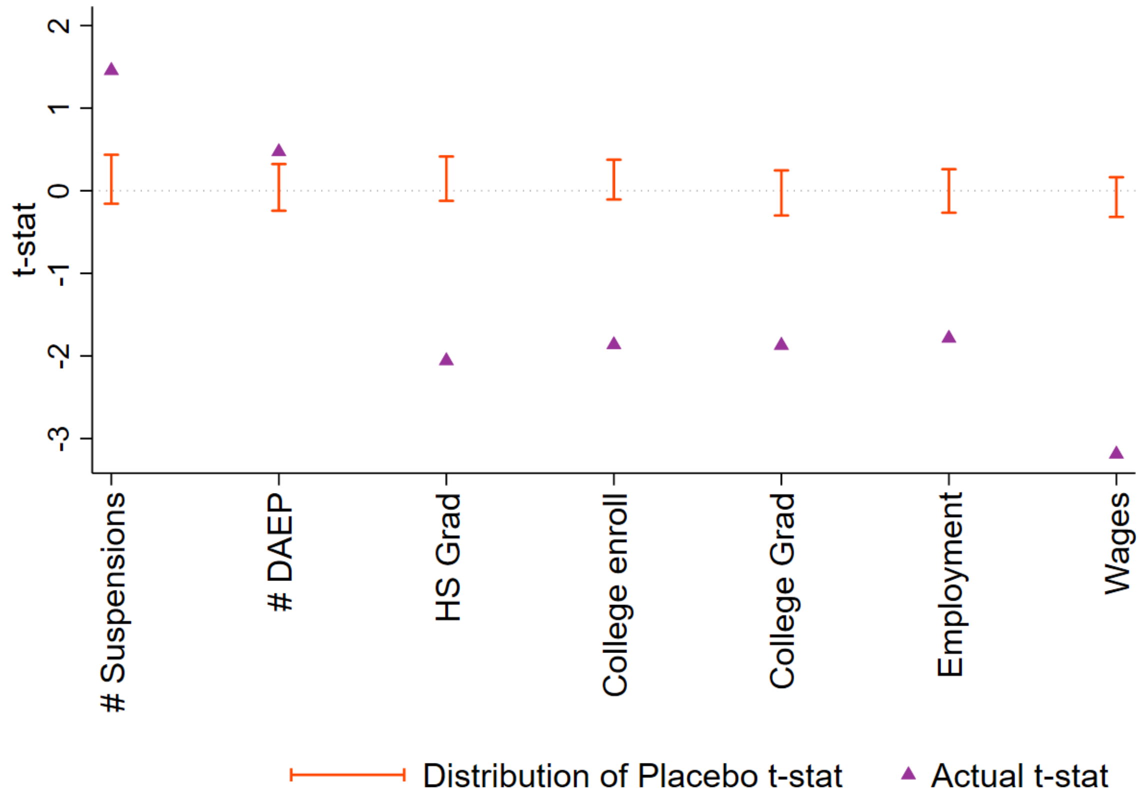
Notes: Figure 10 shows the balance between disruptiveness on students' pre-determined demographic, academic, and disciplinary characteristics. The figure on the left shows the raw correlation between student characteritic and peers' diruptiveness without any controls or fixed effects. On right, figure shows the correlation after inclusion of fixed effects i.e. DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, and DAEP $\times$ duration-bin FEs. Each coefficient plot corresponds to a separate regression equation with outcome variables denoted by the row headers. Standard errors are clustered at the DAEP level. *Sample:* High schools students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 11: Alternate Specifications and Treatments



Notes: Figure 11 summarizes results from a battery of robustness tests. Columns 1-2 shows the impact of peers' disruptiveness (coefficient β from equation 1) on disciplinary outcomes, columns 3-5 for educational outcomes and columns 6-7 for labor market outcomes. Each coefficient comes from a separate regression equation, where outcomes are denoted by the column header and specification by the row header. Row 1 (denoted by S0) shows the coefficient plot for impact of peers' disruptiveness corresponding to all the main outcomes. Rows 2-4 i.e. specifications S2, S3 and S4, show results from the alternate specifications. Specification 1 (row 2) re-estimate the peer effects for each outcome by including controls for peer characteristics such as race, gender, test scores, and reason for removal, specification S2 (row 3) includes sending school fixed effects, specification S3 (row 4) shows results for outcomes when peers are determined based on students' actual days of placement instead of assigned days of placement, and specification 4 (row 5) shows results from alternate measure of peers' disruptiveness i.e. number of *days* suspended in the past instead of number of times suspended. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure 12: RANDOMIZATION INFERENCE



Notes: Figure shows the result from randomization inference exercise for a sample of high-school students. For each outcome, randomization inference is conducted by running 1000 regressions with placebo treatments. For this, we create a placebo treatment variable by randomizing the peers' average yearly past suspensions for each student in the sample. We then estimate the treatment effects for an additional 1000 times corresponding to each placebo treatment. We repeat this exercise for each outcome in the analysis. For each outcome denoted on the x-axis, the range of placebo betas is denoted by the confidence interval band, whereas the actual treatment coefficient is given by the triangles. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

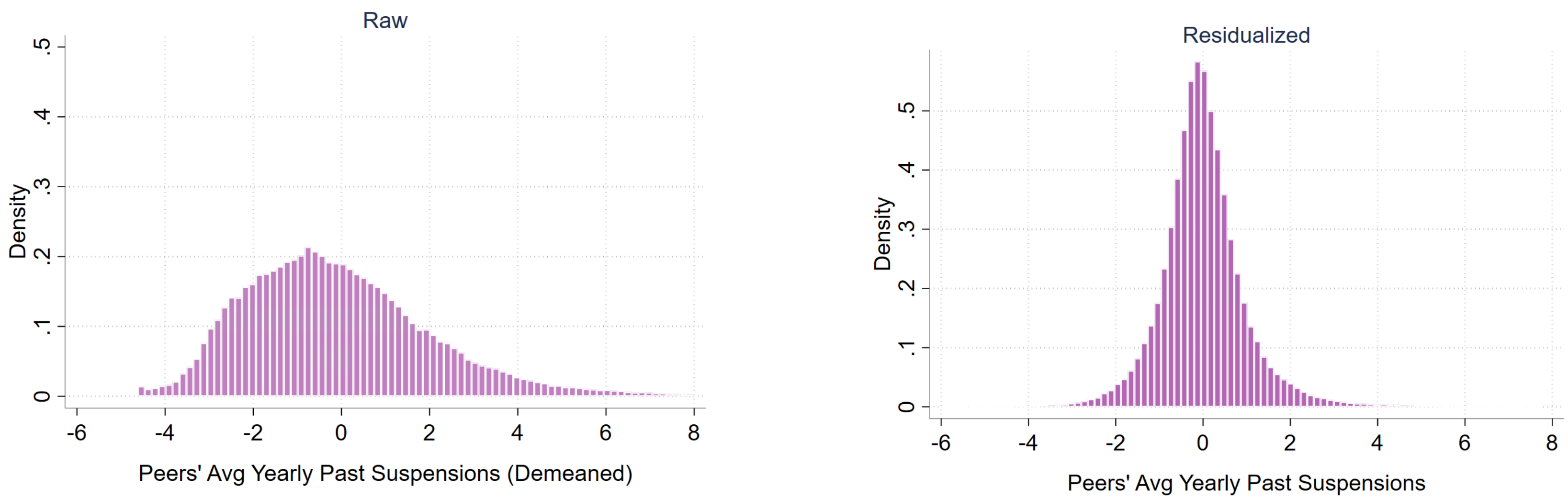
ONLINE APPENDIX

for

"Disruptive Interactions: Long-run Peer Effects of Disciplinary Schools"

A Appendix Tables and Figures

Figure A.1: Raw and Residualized Variation in Peers' Disruptiveness

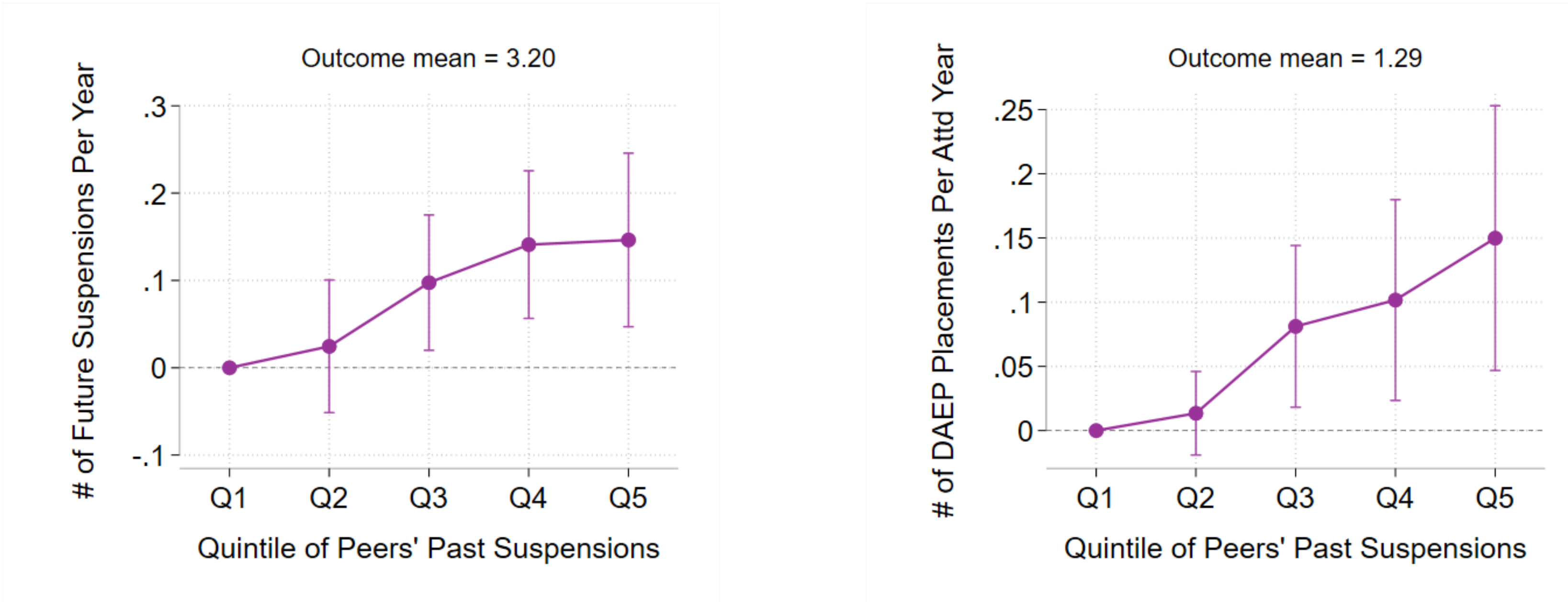


(a) Raw Variation

(b) Residual Variation

Notes: Figure shows the distribution of peers' average disruptiveness (proxied by their average yearly past suspension counts) for students in the main sample. Figure A.1a shows the raw demeaned raw variation in peers' average yearly past suspension, whereas A.1b the residualized variation in peers' disruptiveness after controlling for fixed effects in the main estimating equation 1 i.e. DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.2: Impact on Future Disciplinary Outcomes - Sample with some future removal

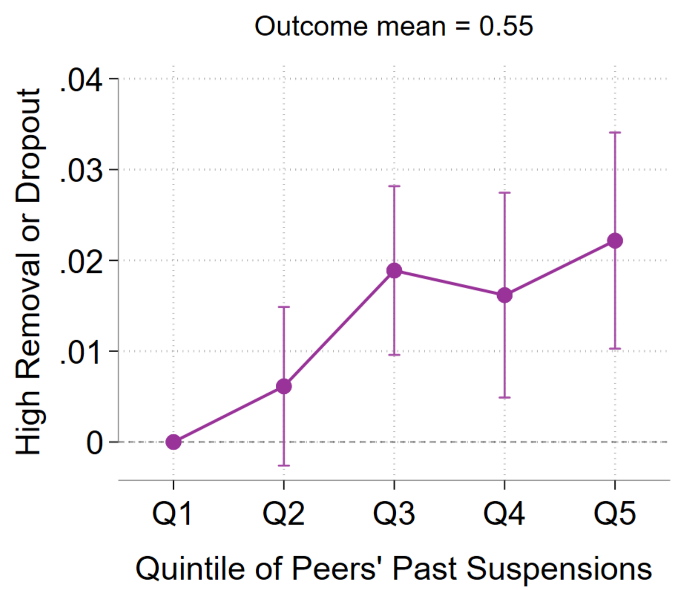


(a) Future Suspensions

(b) Future DAEP Placements

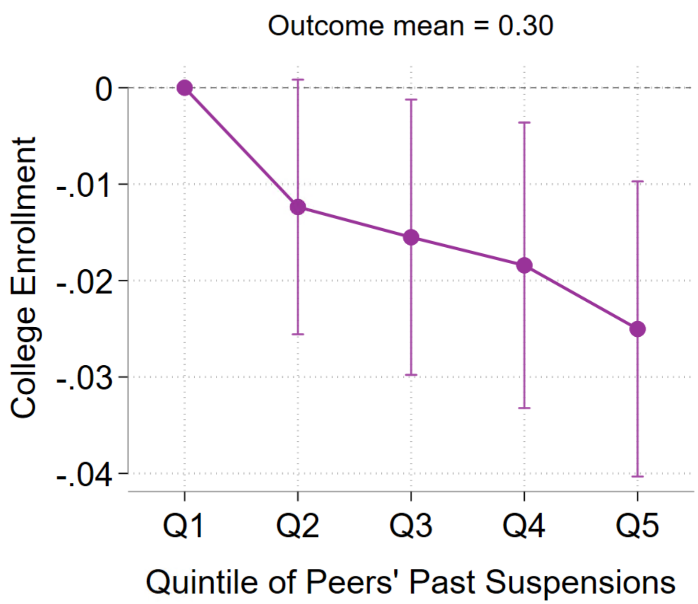
Notes: Figure shows the impact of peers' disruptiveness on students' subsequent disciplinary outcomes for sample of students with some non-zero future removal. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes students' future removals. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.2a plots the impact on students' future suspensions per year, whereas A.2b shows impact on future DAEP placements per year. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018, who return to public schools after their DAEP exit and have some non-zero future removal . *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.3: IMPACT ON PROPENSITY OF HIGH REMOVAL RATE OR DROPOUT

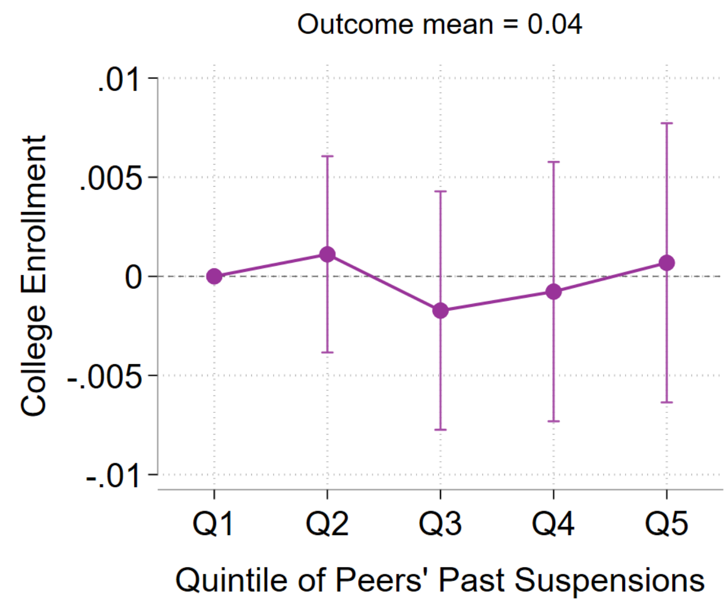


Notes: Figure shows the impact of peers' disruptiveness on students' propensity to either have high removal rates or dropout of school. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes propensity of high removal rate or school dropout, where high removal is measured by a dummy which takes value = 1 if $n(suspension) > p(50)$ & $n(DAEP) > p(50)$ and school dropout = 1 if the student did not graduate from Texas high school. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.4: IMPACT ON 2-YEAR AND 4-YEAR COLLEGE ENROLLMENT



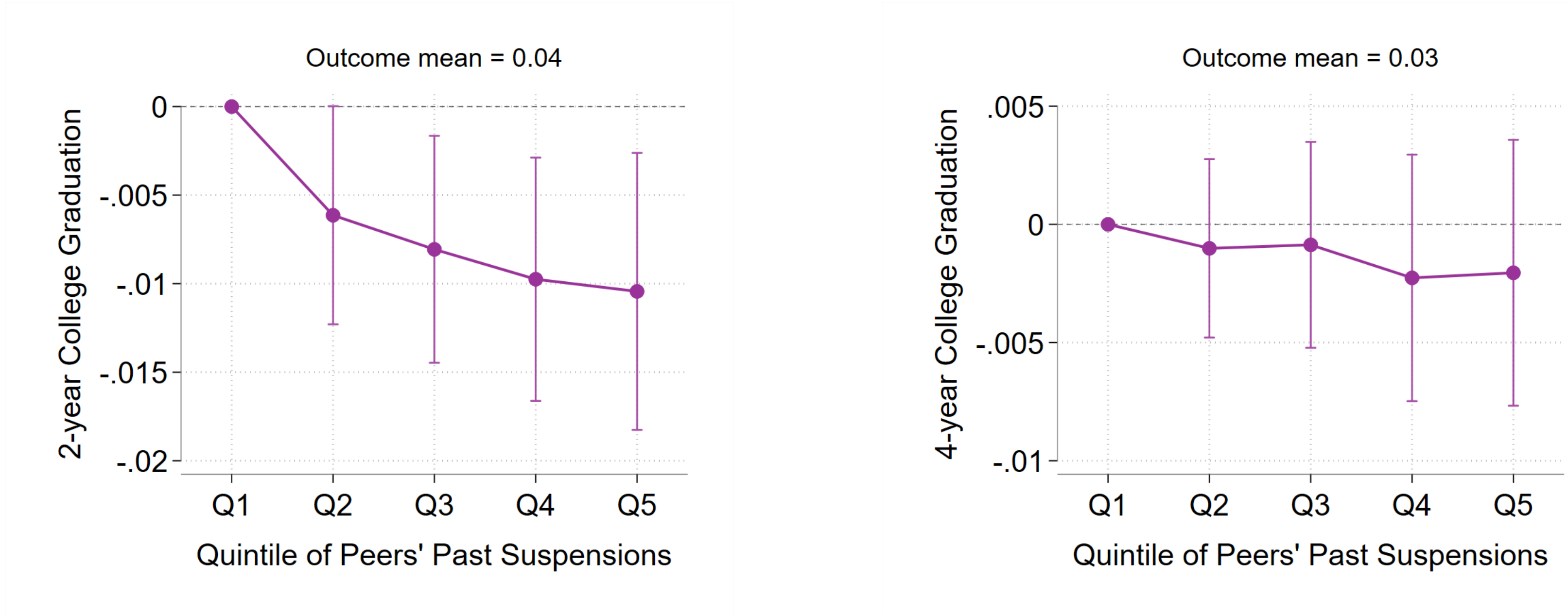
(a) 2-YEAR COLLEGE ENROLLMENT



(b) 4-YEAR COLLEGE ENROLLMENT

Notes: Figure shows the impact of peers' disruptiveness on students' college enrollment separately for 2-year and 4-year colleges. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes college enrollment. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.4a plots the impact on enrollment at 2-year colleges, whereas A.4b shows the impact on enrollment at 4-year colleges. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast of age 23 by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.5: Impact on 2-year and 4-year College Graduation

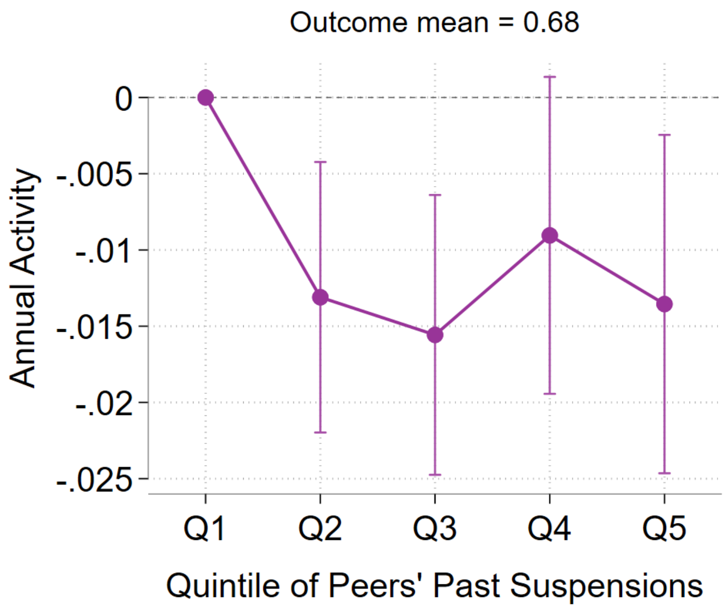


(a) 2-year College Graduation

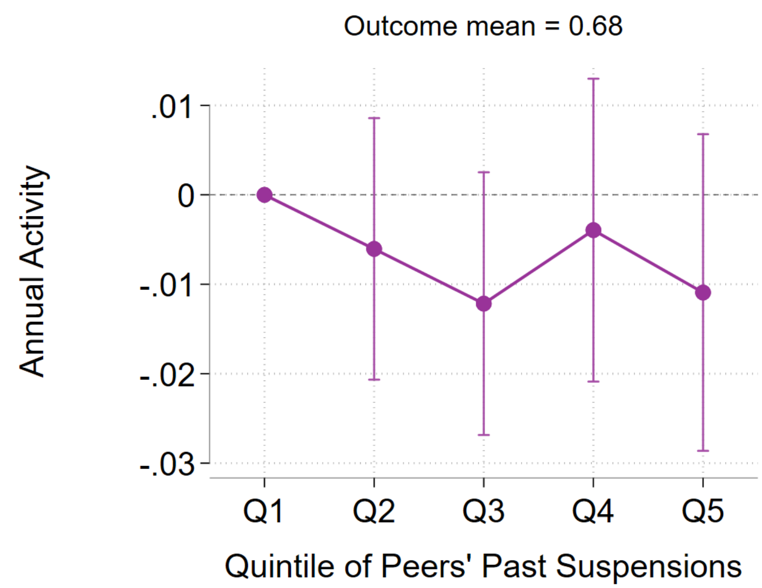
(b) 4-year College Graduation

Notes: Figure shows the impact of peers' disruptiveness on students' college graduation separately for 2-year and 4-year colleges. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes college enrollment. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.5a plots the impact on graduation from a 2-year college, whereas A.5b shows impact on graduation from a 4-year college. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018 and atleast of age 23 by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.6: Impact on Work Activity, by Different Age-Brackets



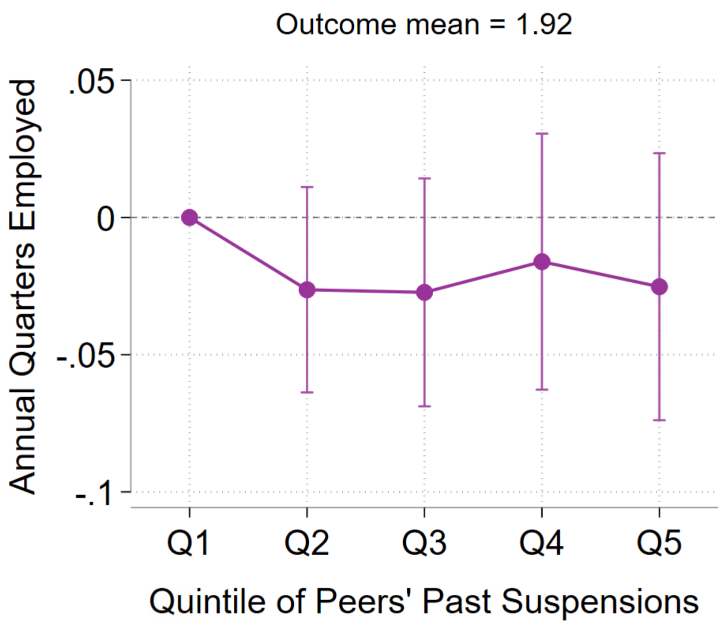
(a) Age Bracket: 18-22 years



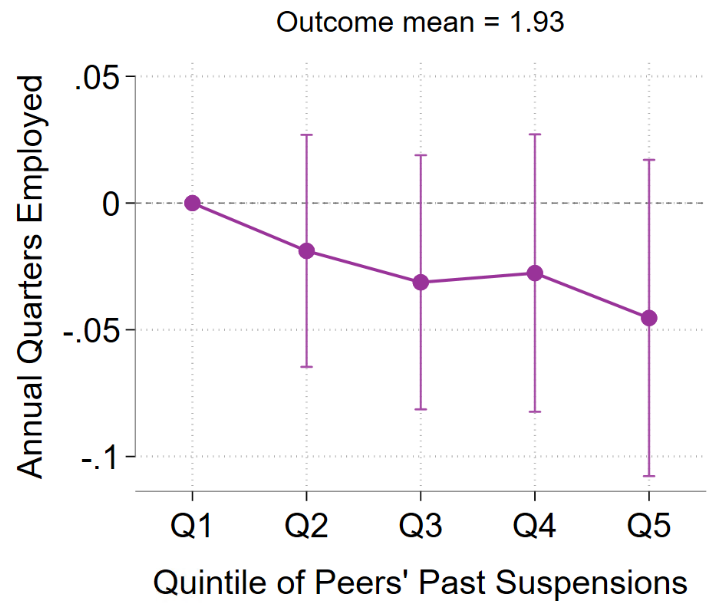
(b) Age Bracket: 23-27 years

Notes: Figure shows the impact of peers' disruptiveness on students' annual activity rate, by different age brackets. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' annual activity rate. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.6a plots the impact on the average annual quarters of employment at age 18-22, whereas A.6b shows impact at age 18-27. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.7: IMPACT ON EMPLOYMENT, BY DIFFERENT AGE-BRACKETS



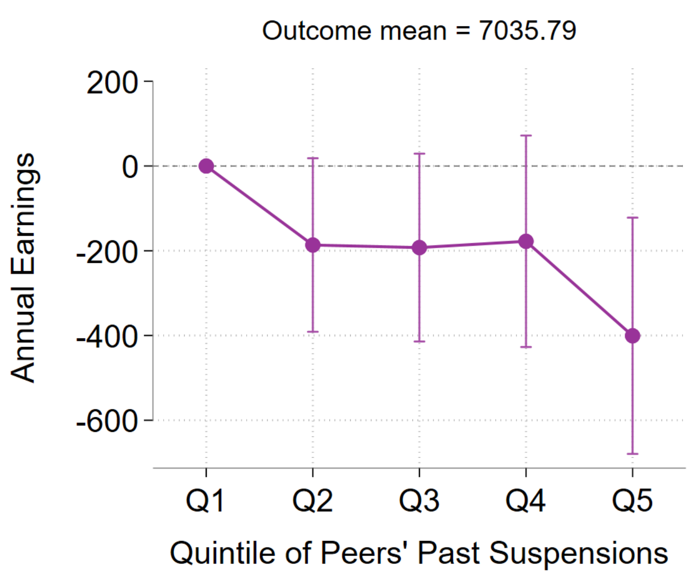
(a) AGE BRACKET: 18-22 YEARS



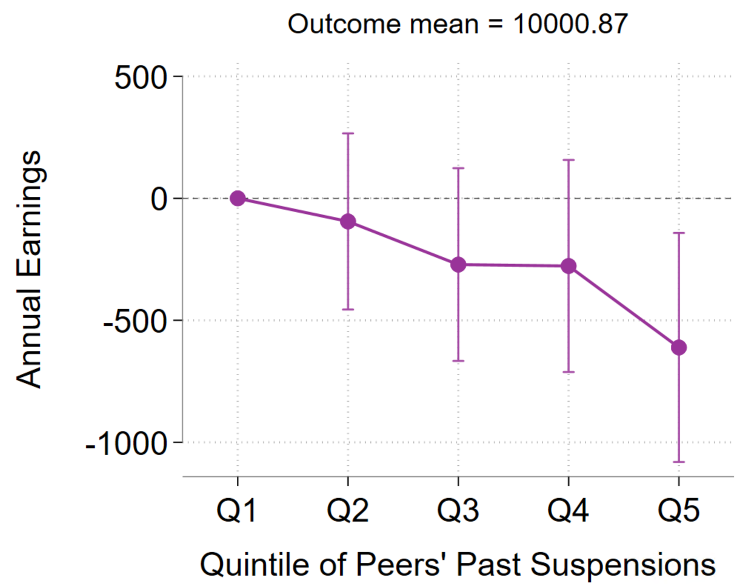
(b) AGE BRACKET: 18-27 YEARS

Notes: Figure shows the impact of peers' disruptiveness on students' employment, by different age brackets. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' end of school outcomes. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.7a plots the impact on the average annual quarters of employment at age 18-22, whereas A.7b shows impact at age 18-27. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.8: Impact on Earnings, by Different Age-Brackets



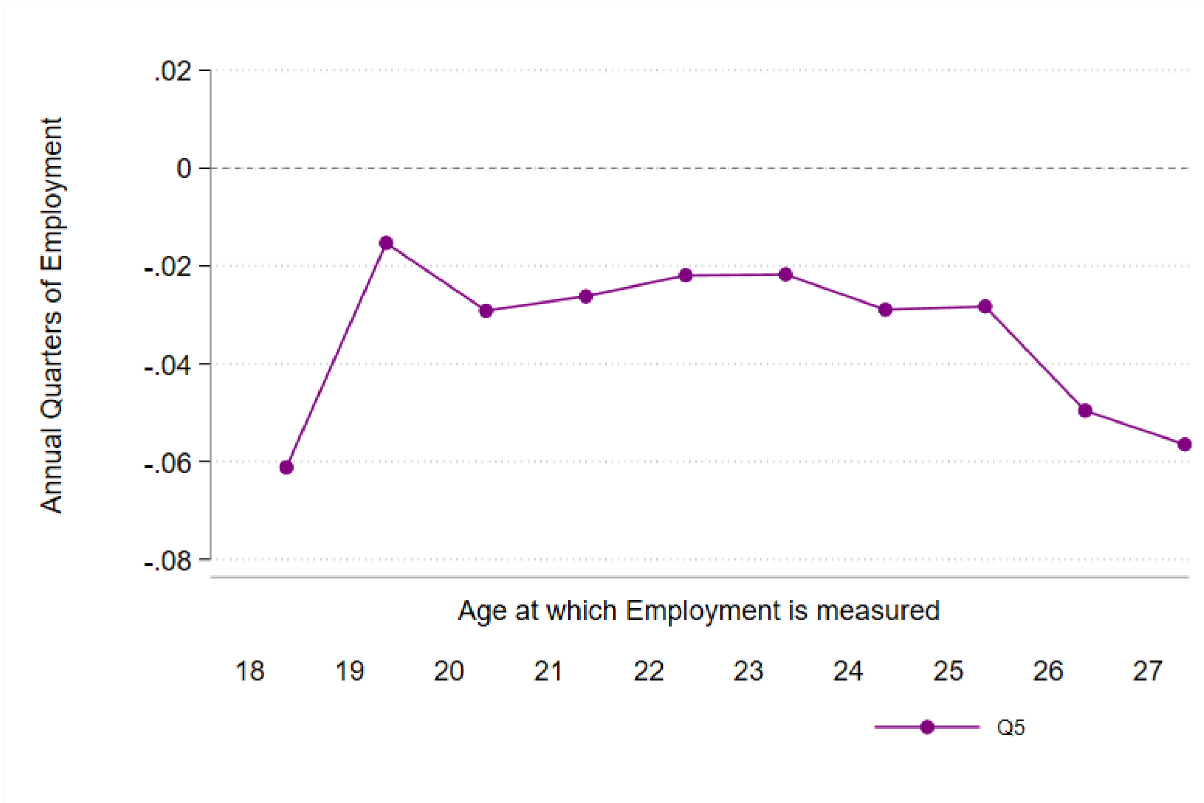
(a) Age Bracket: 18-22 years



(b) Age Bracket: 18-27 years

Notes: Figure shows the impact of peers' disruptiveness on students' earnings, by different age brackets. The x-axis denotes the quintile measure of peers' disruptiveness, where Q1 corresponds to the least disruptive peers and Q5 corresponds to the most disruptive peers. The y-axis denotes the measure of students' earnings. Each quintile shows impact of peers' disruptiveness relative to the omitted quintile, Q1. A.8a plots the impact on the average annual earnings at age 18-22, whereas A.8b shows impact at age 18-27. All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.9: Age-Employment Profile



Notes: Figure plots the impact of peers' disruptiveness on students' employment at each age between 18-27, where employment is measured by number of quarters employment at that age. The x-axis shows age at which employment is measured. The y-axis denotes age-specific employment measure. Each point on the y-axis corresponding to a given age on the x-axis comes from a separate regression (equation 2). For each age, figure shows the impact corresponding to highest quintile (Q5) of peers' disruptiveness relative to Q1 (omitted). All regressions control for DAEP $\times$ Year FEs, School-term FEs, Reason-for-removal FEs, DAEP $\times$ duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.10: AGE-EARNINGS PROFILE

Notes: Figure plots the impact of peers' disruptiveness on students' annual earnings at each age between 18-27. The x-axis shows age at which earnings is measured. The y-axis denotes age-specific annual earnings. Each point on the y-axis corresponding to a given age on the x-axis comes from a separate regression (equation 2). For each age, figure shows the impact corresponding to highest quintile (Q5) of peers' disruptiveness relative to Q1 (omitted). All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

B Additional Analysis

Table A.1: HETEROGENEOUS IMPACT BY RACE AND GENDER

	# of Future Suspensions per Year (1)	# of Future DAEP removal per Year (2)	High-School Graduation (3)	College Enrollment (4)	College Graduation (5)	Activity Per Year (age 23-27) (6)	Employment Quarters (age 23-27) (7)	Earnings Per Year (age 23-27) (8)
Black = 1, else 0								
Peer's Past Suspensions Counts × Black	0.0489**	0.0114**	0.0051**	0.0036	0.0016	-0.0012	-0.0568	-44.5609
	(0.020)	(0.006)	(0.002)	(0.003)	(0.001)	(0.003)	(0.048)	(73.024)
Mean of Dep Var	1.95	0.50	0.50	0.34	0.07	0.67	9.93	13251.36
Observations	183340	137949	113503	113530	113530	63096	63096	63096
Male=1, else 0								
Peer's Past Suspensions Counts × Male	0.0304**	0.0130**	0.0021	-0.0005	0.0003	-0.0025	-0.0580	-61.0463
	(0.014)	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)	(0.068)	(146.520)
Mean of Dep Var	1.95	0.50	0.50	0.34	0.07	0.67	9.93	13251.36
Observations	183340	137949	113503	113530	113530	63096	63096	63096

Notes: Table shows the heterogeneous effect of students' race and gender by peers' disruptiveness on student's subsequent disciplinary outcomes (columns 1-2), educational attainment (columns 3-6), and labor-market outcomes at age 23-27 (columns 7-9). In top panel, *Black* = 1 if student's race is black, else 0. Similarly, in bottom panel, *Make* = 1 if student's gender is male, else 0. Each column corresponds to a separate regression equation with outcome variables denoted by the column headers. All regressions control for DAEP × Year FEs, School-term FEs, Reason-for-removal FEs, DAEP × duration-bin FEs, and students' own race, gender, past test score, past suspension, and sending-school removal rates. Standard errors are clustered at the DAEP level. *Sample:* High-school students placed at DAEPs between 2004-2018. Columns 1 and 2 further restricts sample to students who ever return to public schools after exit from the DAEP, and columns 3-5 to those who are atleast 23 years in age by 2019, and columns 6-8 to those who are atleast 27 years in age by 2019. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system. *Significance:* *p $<$ 0.10, **p $<$ 0.05, ***p $<$0.01.

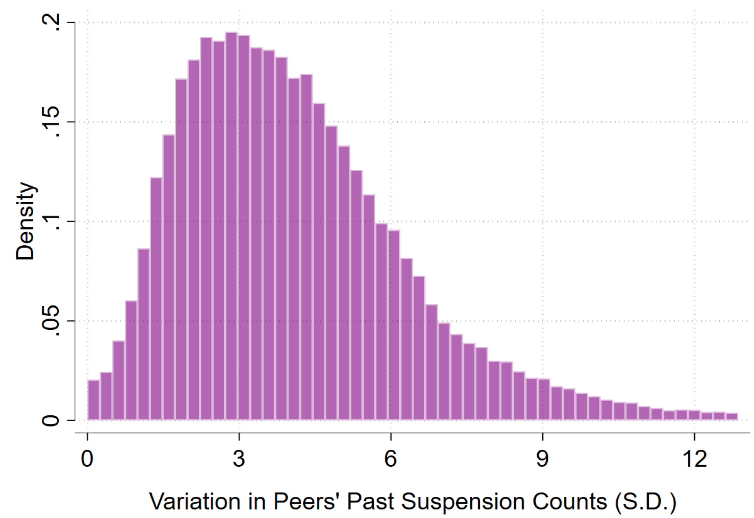
C.1. Propensity Score Matching: Impact of DAEP Placements

Our main results provide estimates for peer effects conditional on students' placement at a DAEP. However, it is not informative of the impact of DAEP placement in itself. Hence, as an additional exercise to understand the impact of being placed at a DAEP on students' outcome, we do a propensity score matching exercise. For this, we take all the students in Texas public schools between 2004-2018 who are placed at the DAEP for the first time. This is our treatment sample. Then for student in the regular classroom i.e. control sample, we generate a propensity of them being based in the treatment group based on their past suspensions, grade, past test scores, race, gender, economic status, special ed status, age. Using this propensity score, we then compare the treatment and the control group and estimate the treatment effect of being placed at a DAEP. We find that DAEP placement leads to 25 pp lower high school graduation for students, with ($ATT_{Control}$= 0.77 , $ATT_{Treatment}$= 0.52).

However, these results are more suggestive than causal evidence as inference from propensity score matching methods suffers from the issue that the remaining unmeasured confounding variables may still be present, thus leading to biased results. Nonetheless, the results provide some evidence that students who are similar in observable characteristics but are not sent to DAEPs have better outcomes than those who are sent to DAEPs. This is in line with the findings from Bacher-Hicks, Billings and Deming (2019) that uses variation in school districts' propensity to suspend students and shows that students who are suspended more often have worse future outcomes compared to their counterparts.

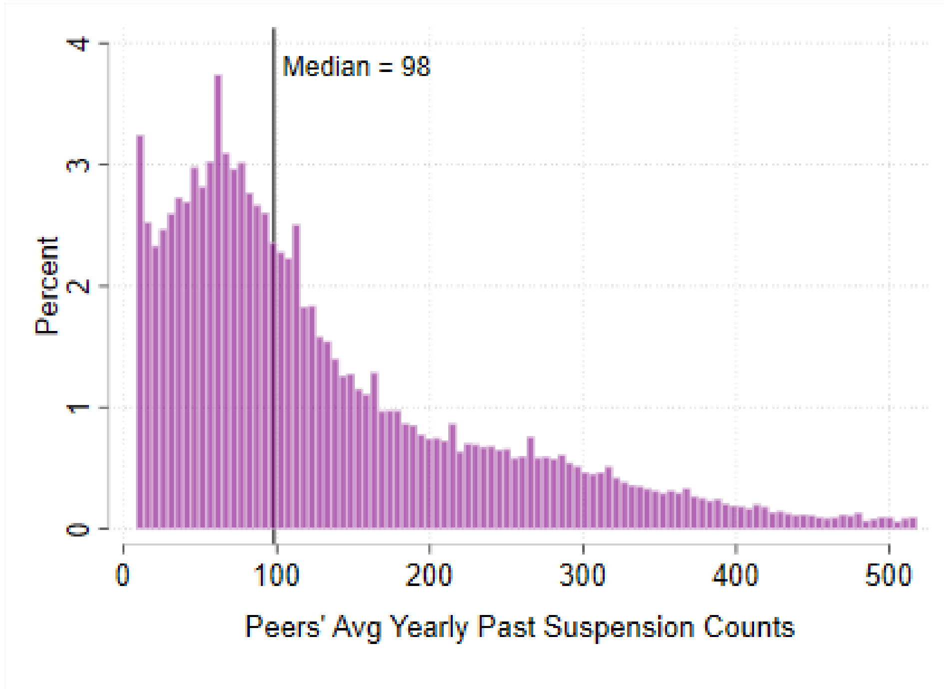
C Miscellaneous Figures

Figure A.11: Distribution of Dispersion (SD) in Peers' Average Disruptiveness



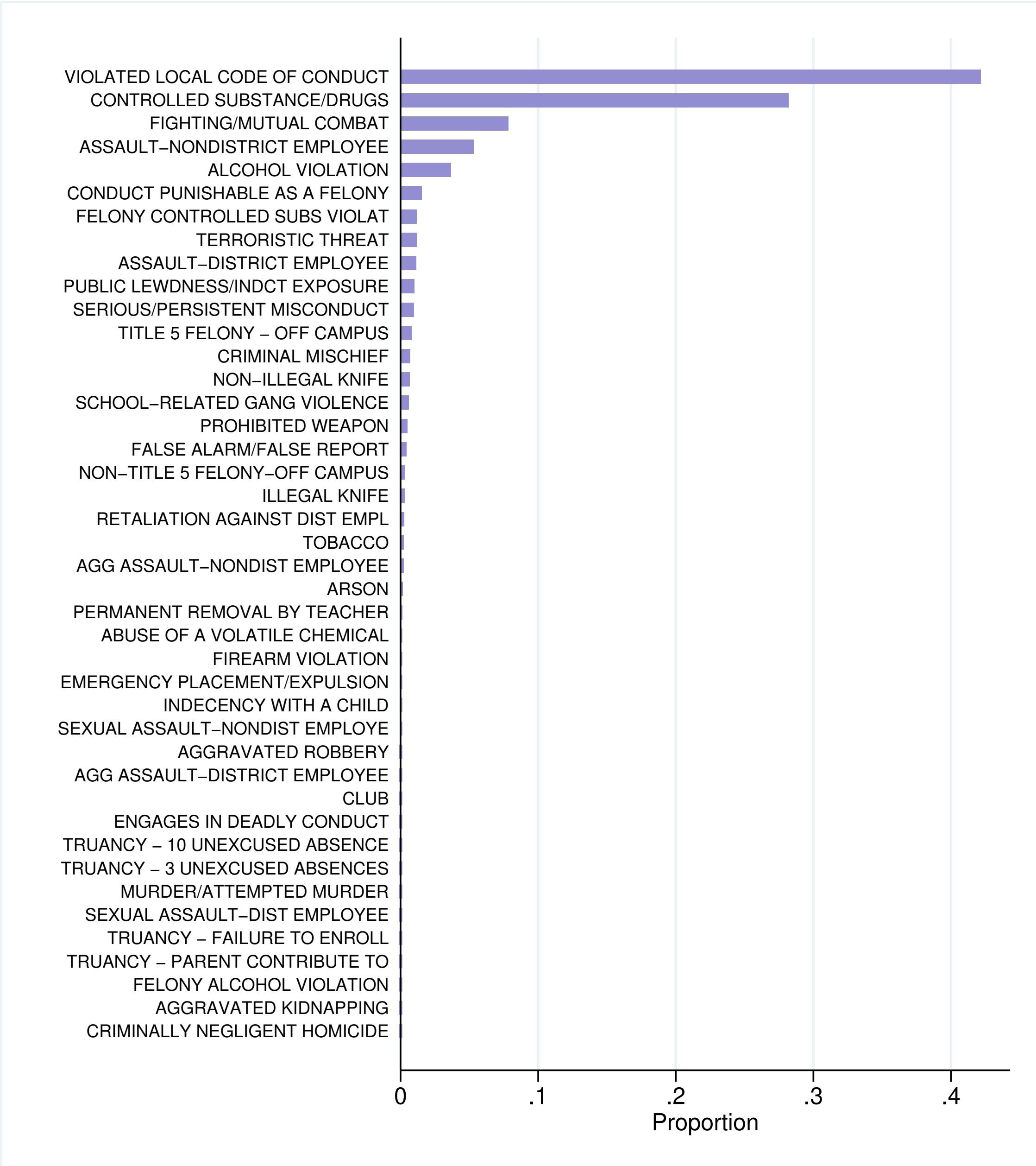
Notes: Figure shows the distribution of standard deviation in peers' disruptiveness for students in the main analysis sample, where peers' disruptiveness is proxied by their average annual past suspension counts.*Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.12: DISTRIBUTION OF THE NUMBER OF PEERS



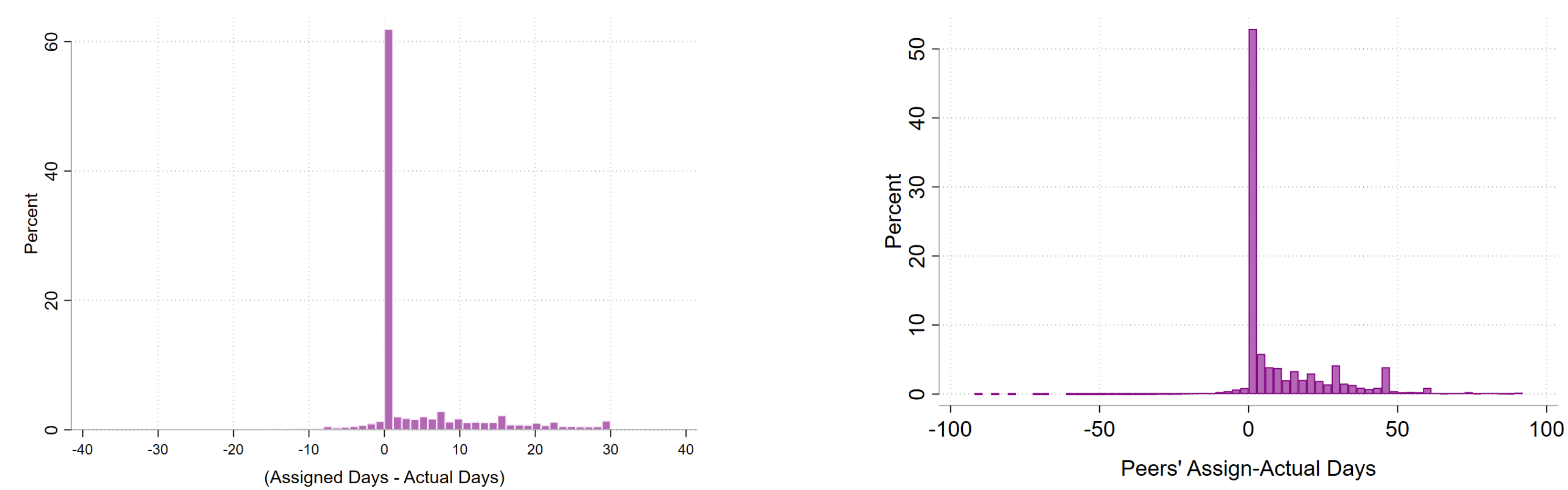
Notes: Figure shows the distribution of the number of peers for students in the main analysis sample. Vertical black line shows the median of the distribution. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.13: PROPORTION OF STUDENTS, BY REASONS FOR REMOVAL TO DAEPs



Notes: Figure shows the proportion of students who are removed for different reasons. The y-axis denotes the various reasons for which the students are removed to DAEPs, whereas the x-axis shows the proportion of student removed for each listed reason. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.14: DIFFERENCE BETWEEN ASSIGNED AND ACTUAL DURATION OF PLACEMENT

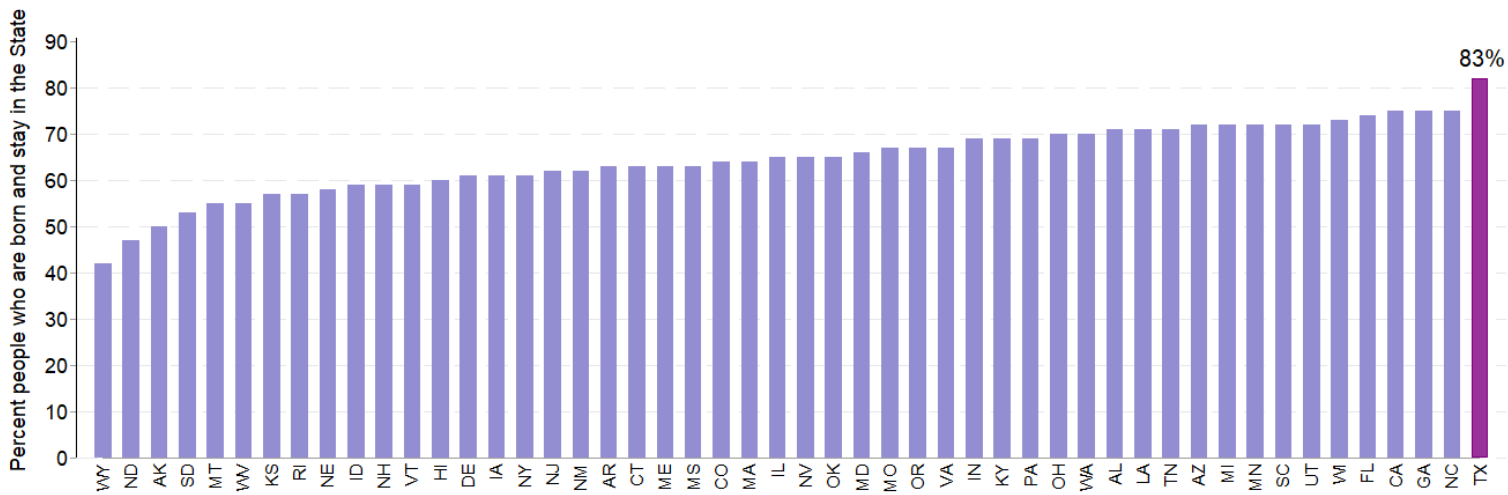


(a) STUDENT

(b) PEERS

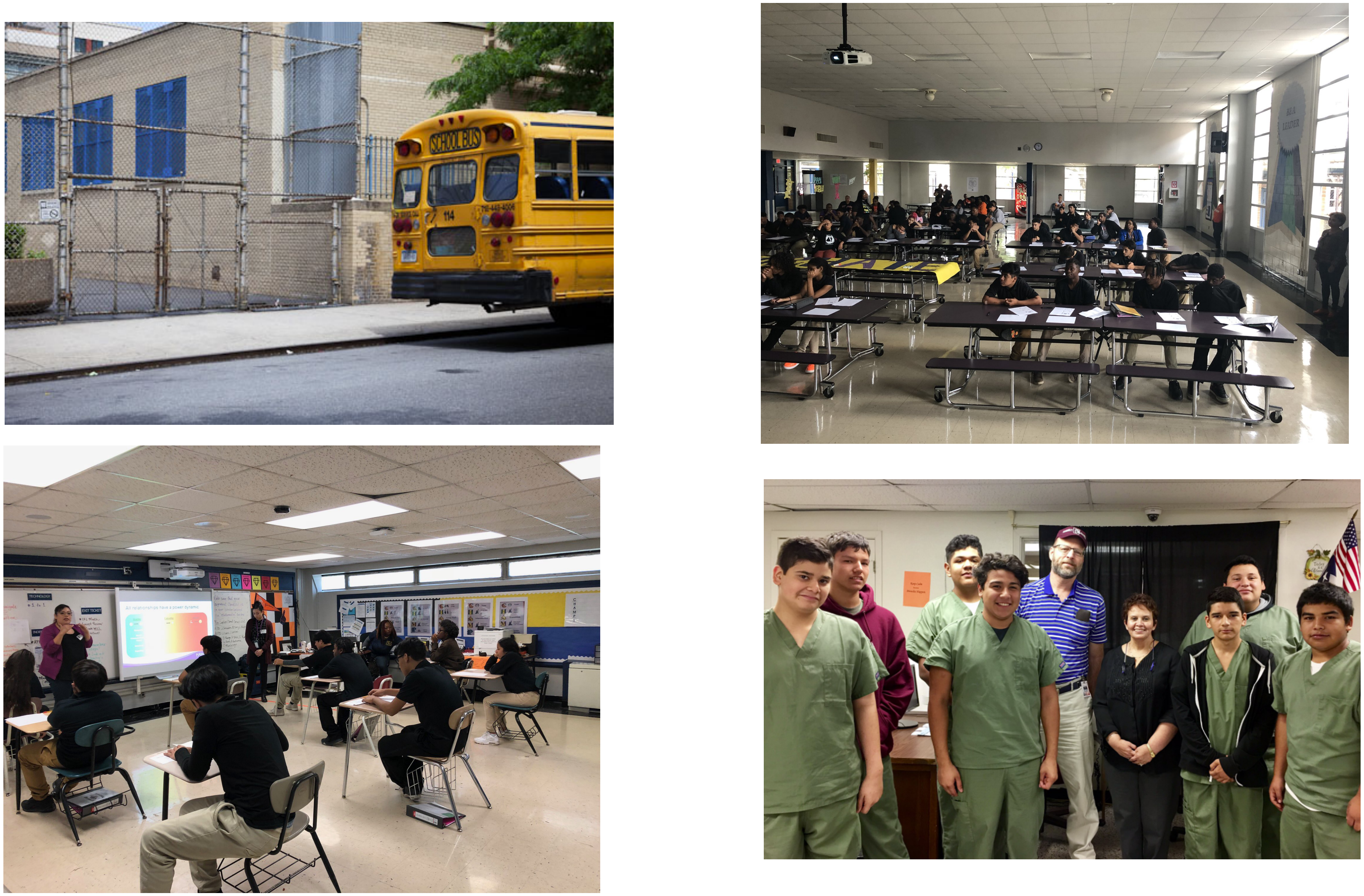
Notes: **Notes:** Figure shows the distribution of the difference between assigned and actual days of removal to DAEPs for students in the main analysis sample (figure A.14a) and their peers (figure A.14b. The x-axis plots the difference in the assigned and actual days of placement at DAEPs, whereas y-axis shows the percent of students or peers. *Sample:* High-school students placed at DAEPs between 2004-2018. *Source:* Authors' calculation using restricted-use Texas administrative data on students in public education system.

Figure A.15: Population Retention Rate of States for People Born in the Same State



Notes: Figure shows the retention rate for state-born population, by states in the US. Figure shows that the Texas has one of the highest percentage of retention its natives (since 2000) in the country. *Source:* Authors' calculation using data from NYT (2014). Original source: Census microdata obtained from ipums.org at the University of Minnesota Population Center.

Figure A.16: PHOTOS FROM DAEPS IN TEXAS



Notes: The pictures above show different aspects of DAEP environment. Picture on the top-left shows the closed DAEP campus with high fences; on top-right and bottom-left are photos of students attending joint classes on careers and social behavior; and on the bottom-right is a photo shows that students at DAEPs are required to wear specific uniform while on campus.