THE IMPACT OF EVICTION ON STUDENT DISPLACEMENT

An Atlanta Case Study

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Literature Review

Introduction

Unexpected school changes place affected students, their classmates, their teachers, and the school as a whole at a disadvantage. Student achievement, school completion, and instructional quality are all compromised when classrooms regularly lose and gain new students during the school year. High mobility erodes the quality of learning and engagement of students and faculty alike. As school quality and engagement decrease, school turnover increases, making it very difficult for a school with high mobility to reverse its trajectory.

American families display high residential mobility while American children display high school mobility. The United States Census Bureau's most recent estimates find that over 45.6 million people moved between 2017 and 2018 (US Census Bureau, 2018). A 2010 report by the Government Accountability Office found that 13 percent of students experienced four or more school changes by the time they reached high school (US General Accounting Office, 1994). These highly mobile students were more likely to be poor or black than students who changed schools twice or less. The GAO study also found that students from renter households represented 39 percent of the most mobile students. High-poverty schools are more likely to have high mobility rates, widening existing deficits relative to more affluent schools. These schools may experience a turnover of 50 percent of their students during one school year (Hartman and Squires, 2009). Schools with larger populations of migrant or homeless students or students in foster care are also more likely to experience high mobility (Parra and Martinez, 2013).

Research on the effects of student mobility has extensively documented its negative impact on students, teachers, schools, and districts. Studies on the causes of student mobility have distinguished between different types of school changes and drawn conclusions about their relative severity and the ability of schools and policymakers to respond to each type. School changes caused by involuntary residential moves in response to unexpected life events that occur during the school year have the most significant negative impact. The difficulty of quantifying how often moves are caused by unexpected life events and which of those events are most impactful has impeded the formation of strong causal inferences into causes of student mobility.

This paper will measure the relationship between one of the most common causes of involuntary moves, eviction, and school mobility, using the City of Atlanta and Atlanta Public Schools (APS) as a case study. School districts in metro Atlanta have the highest mobility rates in the state of Georgia when controlling for the presence of a military base and APS has consistently been in the top 10 of all districts in Georgia in terms of mobility rate (Beaudette, 2014). The City of Atlanta had an eviction filing rate of 17.62% compared with a national average of 6.12% and an eviction judgment rate of 5.12% compared with a national average of 2.34% (Eviction Lab). Atlanta's poverty rate was 54% greater than the national average in 2018, according to the Census Bureau (US Census Bureau, 2018). This housing and economic insecurity is driven by rates of racial and economic segregation that are higher than most American cities (Acs et al., 2017)

Despite being a predominantly black city, Atlanta is one of the most racially segregated cities in America, with neighborhood patterns that still reflect those caused by de joure segregation (Bischoff and Reardon, 2014). Compounding these racial and economic disparities are Atlanta's low levels of intergenerational mobility and high levels of economic inequality. Children born in poverty in Atlanta are more likely to remain in poverty than nearly any other large American city and the gap between the wealthiest and poorest residents is wider than any other city in the country (Chetty et al., 2016). School attendance zones tend to reflect the racial and economic disparities of the neighborhoods they serve, and Atlanta is no exception (Orfield et al., 2014). Schools already struggling with the effects of segregation and structural inequality have these challenges exacerbated by high student turnover and the students driving that turnover belong to groups with the highest barriers to upward mobility. We know that eviction has the same disproportionate impact on poor communities and communities of color (Teresa, 2018).

We also know that eviction is a major cause of the types of involuntary, residential moves that have the most severe negative impact on school mobility. These moves also tend to be to neighborhoods with higher poverty and crime rates (Desmond and Shollenberger, 2015). This paper seeks to build on these commonalities between eviction and high student mobility by quantifying the impact of eviction on student displacement. This approach first necessitates a more thorough examination of the causes and consequences of student mobility and eviction as well as their respective dimensionalities. Careful consideration of both the overlapping and diverging causes and effects of each phenomenon is necessary to ensure that this study models the relationship between eviction and student displacement driven by residential moves as specifically as possible. The remainder of this section will differentiate student mobility caused by involuntary residential moves from student mobility as a whole and identify different mechanisms of eviction before discussing key connections between eviction and school-aged children identified by existing research.

Dimensions of School Mobility

Fundamentally, student mobility is the process of students entering and exiting schools. Despite recent increases in charter school enrollment and school choice programs, the majority of public school students in the United States attend their local school. School districts draw boundaries, normally called attendance zones, around each school, and any child living within the zone for a particular school may enroll there. Due to this system, the bulk of student mobility is caused by individual moves that place students in a different attendance zone or an entirely different district. While district structure dictates some school changes, such as a student moving from elementary to middle school, most school changes are initiated by families and driven by factors unrelated to school (Welsh, 2017).

It is difficult to accurately determine the motivations behind school changes at a scale that would yield sufficient data to support causal claims (Welsh, 2017). Research on school mobility has generated some strong conclusions about its impact, but the challenge of assembling and analyzing longitudinal educational datasets and the difficulty of accurately interpreting the reasons behind decisions that result in school changes limits the scope of those conclusions (Welsh, 2017). These limitations also inhibit understanding of the causes of school mobility. Existing research succeeds in broadly categorizing some of the main causes of school change but struggles to compile sufficient evidence regarding the magnitude and distribution of these causes. Consequently, the bulk of school mobility research primarily focuses on its impact on student performance and child development.

Studies of the impact of high mobility typically use large longitudinal datasets containing the educational outcomes of students who experience a school change. Surveys of student outcomes at the national, state, and local level show that student mobility most strongly impacts standardized test scores and graduation rates. Some studies also suggest a negative impact on student behavior, but these findings are less consistent across the literature. The magnitude of these effects increases with additional school changes (Rumberger, 2003). Some school changes are motivated by the pursuit of a higher quality school or different learning opportunities and it is possible that this type of movement may mitigate some of the negative effects of transitioning to a new school (Maroulis et al., 2019). Low-achieving students are less likely to make these types of positive transfers, though, and more likely to experience involuntary changes during the school year (Welsh, 2017).

Mobility caused by grade promotion is generally separated out from other school changes as this progression is inherent to the nested nature of school geographies. Other school-initiated causes, such as expulsion, school closure, or redistricting are far less common than those initiated by families. Residential moves by families also usually result in a change of school (Spencer, 2017). Consequently, understanding how and why families with children in public schools move is essential to strengthening causal inferences of school mobility. Family-initiated school changes may be voluntary due to events such as job changes or movement to a better home or involuntary due to job loss or eviction, among other factors (Rumberger, 2003). Involuntary moves are more common during the school year, when families, teachers, and school officials have less time and flexibility to respond effectively (Rumberger, 2003).

Structures of Eviction

While eviction, by definition, a tool for forcing residential displacement, it is also a complex process that functions differently depending on the type of landlord, the type of property where the eviction occurs, and the structure of the evicted household, among other factors. In order to effectively predict eviction and model its impact on tenants, recent research has identified different types of evictions and the mechanisms through which they operate. Landlords use evictions differently depending on whether their goal is to actually remove a tenant or to use the threat of that removal to solicit payment. “Serial” evictions are used as a tool to gain legal backing for the collection of rent payments and late fees and are generally not intended to displace tenants (Rumberger, 2003). This type of eviction filing is more common in larger, newer buildings owned by corporate landlords. “Nonserial” filings are used to remove tenants and are more common in smaller buildings that have recently been listed as for sale. They are also associated with a higher level of neighborhood rent burden (Immergluck et al., 2019).

Serial filing rates are increasing as ownership and management of rental properties by corporate landowners become more common. The size of the property investor is associated with higher housing instability due to eviction filings and this pattern is apparent in both multifamily and single family properties (Raymond et al. 2016). Serial filing allows landlords to use the threat of eviction to their advantage without incurring the cost of actually carrying them out. Although the main intention of these filings is not tenant removal, the legal backing of courts creates a power imbalance in favor of the landlord and makes tenants more vulnerable to future removal (Garboden and Rosen, 2019). Regardless of the landlord's intention, tenants may elect to vacate the property to avoid having an eviction added to their record. Eviction not only displaces people from their homes but also creates significant obstacles to finding new housing. Past evictions limit the ability of renters to qualify for housing assistance programs and make them less attractive potential tenants to landlords (Desmond et al., 2013).

Even though serial and nonserial eviction rates continue to rise across the country and marginalize renters at alarming rates, eviction estimates may actually be suppressed due to the omission of "informal" or "non-court" evictions (Lundberg and Donnelly 2019). These evictions occur outside of courts and range from landlords unofficially telling tenants to move without actually filing to the city condemning a building or the landlord entering foreclosure (Desmond and Shollenberger, 2015). Most eviction studies have largely relied on administrative or survey data that does not account for these evictions, however, so informal evictions are less understood (Lundberg and Donnelly, 2019). The development of a method to estimate these types of evictions is essential to calculating more accurate eviction rates and strengthening both causal inferences and estimates of consequences.

Student Mobility and Eviction

As one of the strongest and most preventable causes of involuntary residential displacement, evictions should be central to any effort to reduce school changes resulting from that displacement. There is an established connection between involuntary residential moves and higher student mobility. Data on student mobility is not collected in the same comprehensive fashion as other education data, however, making strong causal inferences difficult (Spencer, 2017). Despite these limitations, certain major drivers, such as eviction, are apparent and merit further study even before more consistent data is compiled. Further research into all causes of student mobility is critical to the improvement of school outcomes. It is well established that low-performing schools serving low-income populations have the highest levels of school mobility and most of student mobility is driven by family-initiated, residential moves (Rumberger, 2003). Far less established in the research are the specific causes of these moves and the share of residential moves caused that are made involuntarily in response to disruptive life events. Advances in research on the impact of disruptive life events on student outcomes may offer a pathway to better understanding of these dynamics. A large body of research also exists around the impact of disruptive events on the development and academic performance of children. Areas of focus in this research range from the structure of families to sudden employment changes and school-initiated events (Cooper et al., 2001; Brand & Simon Thomas, 2014; Temple & Reynonds, 1999). Eviction is both a disruptive life event that often results in a residential move, but its impact on students has not yet been thoroughly explored. Increased attention to the specific effects of evictions on students and their education is essential to addressing the problems caused by frequent school changes at the individual, school, and district level (Welsh, 2017).

Reactive moves made by families due to evictions have received surprisingly little attention given the prominence of eviction in current housing research. Substantial evidence exists to support both the increasing prevalence of eviction among urban renters and the significant impact involuntary moves caused by eviction have on student mobility rates. Additional research describes the negative impact of high student mobility on school achievement. While researchers differ over whether eviction and school mobility should be viewed as symptoms or causes of urban poverty, there is widespread agreement that each has tangible, negative impacts on children and the communities in which they live (Desmond et al. 2013). Evictions lead to homelessness, poor health, loss of work, and an inability to find future housing (Desmond and Kimbro, 2015). A single, planned school change can impede student growth, and multiple, unplanned school changes are associated with increased risk of dropping out and missing developmental benchmarks, lower standardized test scores and decreased engagement and motivation (Rumberger and Larson, 1998). This type of mobility also impedes classroom instruction and drains scarce school resources (Isernhagen & Bulkin, 2011). Moves made in response to disruptive life events disproportionately affect low-income families who rent in disadvantaged neighborhoods (Clark, 2011). Already likely to be at a deficit relative to higher-income classmates, low-income students suffering high residential instability or homelessness perform worse on standardized tests, experience delays in the development of literacy skills, display lower overall school achievement, and are more likely to be chronically absent or drop out (National Research Council, 2010). High residential instability may also lower math achievement and educational and social engagement (Gottfried, 2014).

Involuntary moves are the most disruptive type of residential move and eviction is a major cause of these moves. If public schools are ever to realize their potential to alleviate inequality, every effort must be made to focus all available resources on providing the best possible instruction and support to every student. Frequent and unexpected school changes undermine this goal and will continue to do so until their causes are better understood. The growing body of knowledge around eviction can help to close the gap in understanding of involuntary moves as they relate to student mobility. As foreclosure rates have declined after the housing crisis, research focus has shifted towards eviction as a key driver of housing insecurity. Eviction is one of the main causes of involuntary moves and eviction rates, like school mobility, disproportionately affect low-income households. The presence of children is one of the major predictors of eviction and neighborhoods with higher levels of school age children are more likely to have higher eviction rates (Desmond, 2013). Families with children also face higher rates of eviction judgments, and having those judgments in the public record makes those families more likely to experience additional future evictions (Desmond, 2013). Judgments offer greater potential to predict student displacement as they provide the landlord with the legal justification to take possession of the property. Eviction research demonstrates that the presence of children also increases this residential instability at the household and neighborhood levels (Desmond et al., 2013). Other findings suggest that more than 1 in 6 children born in major American cities experience an eviction by the time they turn 15, meaning that children are both elevating eviction rates and suffering their consequences (Lundberg and Donnelly, 2016). This figure may even be conservative due to the exclusion of informal evictions (Desmond and Shollenberger, 2015). Student mobility also has effects that extend beyond the displaced individual. Schools with high mobility rates display lower overall achievement as a whole, indicating a class- and schoolwide effect regardless of whether an individual student has high mobility (LeBoeuf and Fantuzzo, 2018).

There is a strong implication that schools serving neighborhoods with high eviction rates will suffer from high student mobility and that the presence of children serves to increase eviction rates, but no study has yet quantified such a relationship. The majority of public-school students will make at least one non-promotional change during their school careers, most of those changes are involuntary and family-initiated, and many of those family decisions are reactions to eviction (Rumberger, 2003). Missing from this equation is the magnitude of evictions impact on student displacement. Better understanding of eviction can help schools stabilize their populations by addressing student mobility proactively. Increased recognition of eviction's impact on educational outcomes can also support calls for increased tenant protections and more equitable legal proceedings (Dickinson, 2015).

Driving Questions

This paper identifies eviction as a potential predictor of increased student mobility. As detailed above, it is not only formal evictions, those that involve official court filings, that create this create this mobility. Informal or non-court evictions frequently occur when rental complexes are sold or redeveloped and also lead to tenant removal (Raymond et al. 2016). This analysis also attempts to use identify effective proxies to measure the distribution and intensity of these informal evictions. In doing so, I hope to propose a framework for both quantifying the relationship between eviction and student displacement as well as for estimating the influence of informal evictions within local housing markets. Using a dataset consisting of student withdrawals from Atlanta Public Schools, formal eviction records from the two counties that contain the City of Atlanta, and apartment deed transfer records and multifamily building permits as proxies for informal evictions, I constructed a panel regression model to measure eviction's association with student displacement within the attendance zone boundaries of traditional public schools APS. Charter schools were excluded as their enrollment draw from the entire district and are consequently not subject to the same attendance zone effects.

Data and Methods

Data Selection and Compilation

I began the process of assembling my dataset knowing that I would need to adapt data from multiple geographies to fit attendance zone boundaries in order to analyze student displacement from those boundaries. Table 1 shows the data elements I selected, their sources, and briefly describes any necessary transformations..

Table 1: Data Sources and Transformations

Variable	Description	Source(s)	Transformation(s)

Attendance Zone Boundaries	Spatial files of APS attendance zone boundaries for elementary, middle, and high schools.	Atlanta Public Schools	Data from all below was joined to attendance zone geometry
Eviction Filings & Judgments	Dataset of all evictions for Fulton and DeKalb County for the years 2016 through 2019.	Fulton & DeKalb County Magistrate Courts	Data was web scraped, cleaned, and then geocoded for spatial analysis. Judgments were then filtered out and aggregated at the attendance zone level.
Building Permit Records	Dataset of all building permits issued in the City of Atlanta from 2014 until present including construction cost and total fees paid per permit	City of Atlanta Office of Buildings	Provided as PDF, transformed into tabular data, geocoded, and aggregated at the attendance zone level.
Apartment Deed Transfers	Dataset of Fulton County deed transfer records	CoreLogic	Provided in tabular form with coordinates. Aggregated at attendance zone level.
School Enrollment Data	Measures from Atlanta Public Schools' Full-Time Equivalent (FTE) Count, Including - • School name • Grade level • Date of exit • Date of entry • Withdrawal code • Entry code • Student status (code for if the student is normally enrolled, withdrawn, or has been retained)	Atlanta Public Schools	Provided in raw form in response to an Open Records request. Data was then cleaned, filtered and aggregated at the attendance zone level
Demographic Variables	Neighborhood characteristics including- • Rental occupancy rate • Median household income • Black population share • Share of population between the ages of 5 and 19	American Community Survey 5-Year Estimates	Block group polygons transformed to centroid points, joined to attendance zone boundaries in which they fell, and averaged

The first step in assembling my data and model was deciding how exactly to measure student mobility. Studies on student mobility conducted without access to individual level data have tended to focus on student mobility rates. While calculations vary slightly across states, the general formula for these rates is -

$$\frac{\text{Total Student Withdrawals} + \text{Total Student Entries}}{\text{Total Student Enrollment}}$$

This is the formula that the state of Georgia uses for its publicly available student mobility rates. Georgia's Quality Basic Education Act (QBE) requires its public school systems to report student enrollment in terms of Full-Time Equivalent (FTE) students. The state's funding formula is weighted with this data, and FTE counts take place once in the fall and once in the spring for every school in every district. Each measures total enrollment and student entries, but only the fall count measures withdrawals. I initially structured this paper preparing to use the published school-wide mobility rates, but was able to obtain APS' FTE fall reports for 2017, 2018, and 2019. This allowed me to instead use individual student exits as well as filter out structural exits as the report includes withdrawal codes for students who left their school due to graduation, expulsion, or grade promotion. In accordance with federal privacy laws, personally identifiable information was redacted, so individual student exits were aggregated to the school level and attendance zones used as the unit of observation.

With the study area and dependent variable established, I next compiled my key explanatory variable through the automated web scraping of public case records of eviction judgments from Fulton and Dekalb County Magistrate Courts. All eviction filings were scraped before the case event information was used to separate out judgments The case records do not have a specific indicator for whether a case ended in a judgment or another form of resolution but do contain descriptions of each judicial event in the case proceeding. For example, the record will say whether the judge issued a writ of possession or if the tenant was ejected from the property. Drawing on techniques used in prior research to filter eviction judgments from raw filings data, I selected records that keywords found in event descriptions from cases resulting in judgments such as writ, ejected, possession, and vacated (Raymond, et al. 2016). Spot checking revealed this to be an accurate method for filtering judgments

As described in the literature review, informal evictions occur when landlords unofficially remove tenants. These types of evictions might occur if a landlord wants to raise rents, or if they wish to sell the property. To model this process, I decided to use apartment deed transfers and multi-family building permits as proxy variables. I selected permits for new development, alteration, and land development specifically, as these were the types most commonly associated with the larger developments that change hands frequently and experience higher eviction rates. By this same logic, I filtered out smaller multi-unit dwellings that had been categorized as apartments so that the deed transfer data could more closely model the types of properties that are more prone to eviction. Eviction judgments and building permits were geocoded and joined to the attendance zones that they fell inside of along with apartment transfers. I then used selected American Community Survey (ACS) 5-year for estimates all demographic variables for census block groups lying fully or mostly within APS boundaries. Individual attendance zones were assigned the average value all block groups whose centers fell within their boundaries.

Analysis of the initial dataset showed that various modifications were needed before proceeding to statistical methods. My dependent variable and main predictors were all count variables and my units of analysis were geographic areas of widely varying sizes. When comparing count variables across geographies of varying sizes, it is necessary so normalize them by transforming them into a ratio or percent of a total in order to prevent misleading comparisons. For example, most middle and high schools had higher levels of raw exits than the majority of elementary schools, but this was partly a function of those schools having higher total enrollments. To account for this potential bias, I applied the following transformation to the counts of student exits, eviction judgments, apartment transfers, and building permits for each attendance zone -

$$\frac{\text{Count Variable}}{\text{Total FTE Enrollment for Attendance Zone}} * 100$$

This resulted in ratios per 100 students which were far easier to compare. Table 2 shows the describes the contents and format of the variables in the transformed dataset while Table 3 describes their variation of their summary statistics across the entire dataset.

Table 2: Description and Format of Selected Variables

Name	Description	Format
School Name	Name of school attendance zone being observed	-
Year	Year that fall FTE count was taken	-
School Code	Unique numeric identifier for each school	-
Student Exits	Count of all nonstructural exits by school and year	Count

Student Exits per 100 Students Enrolled at Time of FTE Count	Count of all nonstructural exits by school and year	Ratio
Student Enrollment at Time of FTE Count	Count of all students enrolled at time of fall FTE count by school and year	Count
Eviction Judgments	Count of all eviction judgments by attendance zone and year	Count
Eviction Judgments per 100 Students Enrolled at Time of FTE Count	Count of all eviction judgments by attendance zone and year normalized by student enrollment	Percentage
Eviction Filings	Count of all eviction filings by attendance zone and year	Count
Eviction Filings per 100 Students Enrolled at Time of FTE Count	Count of all eviction filings by attendance zone and year normalized by student enrollment	Ratio
Apartment Deed Transfers	Count of apartment deed transfers in each attendance zone	Count
Apartment Deed Transfers per 100 Students Enrolled at Time of FTE Count	Count of apartment deed transfers in each attendance zone normalized by student enrollment	Ratio
Multi-family Building Permits	Count of multi-family building permits by attendance zone and year	Ratio
Multi-family Building Permits per 100 Students Enrolled at Time of FTE Count	Count of multi-family building permits by attendance zone and year normalized by student enrollment	Ratio
Estimated Rental Occupancy Rate	Percentage of students that are on grade level in math for each attendance zone	Percentage
Median Household Income	Estimated median household income for each attendance zone by year (averaged by block group centroids)	Currency
Black Population Share	Estimated percentage of population that is black for each attendance zone (averaged by block group centroids)	Percentage
Share of Population Between Ages 5 and 19	Estimated percentage of population aged 5 to 19 for each attendance	Ratio

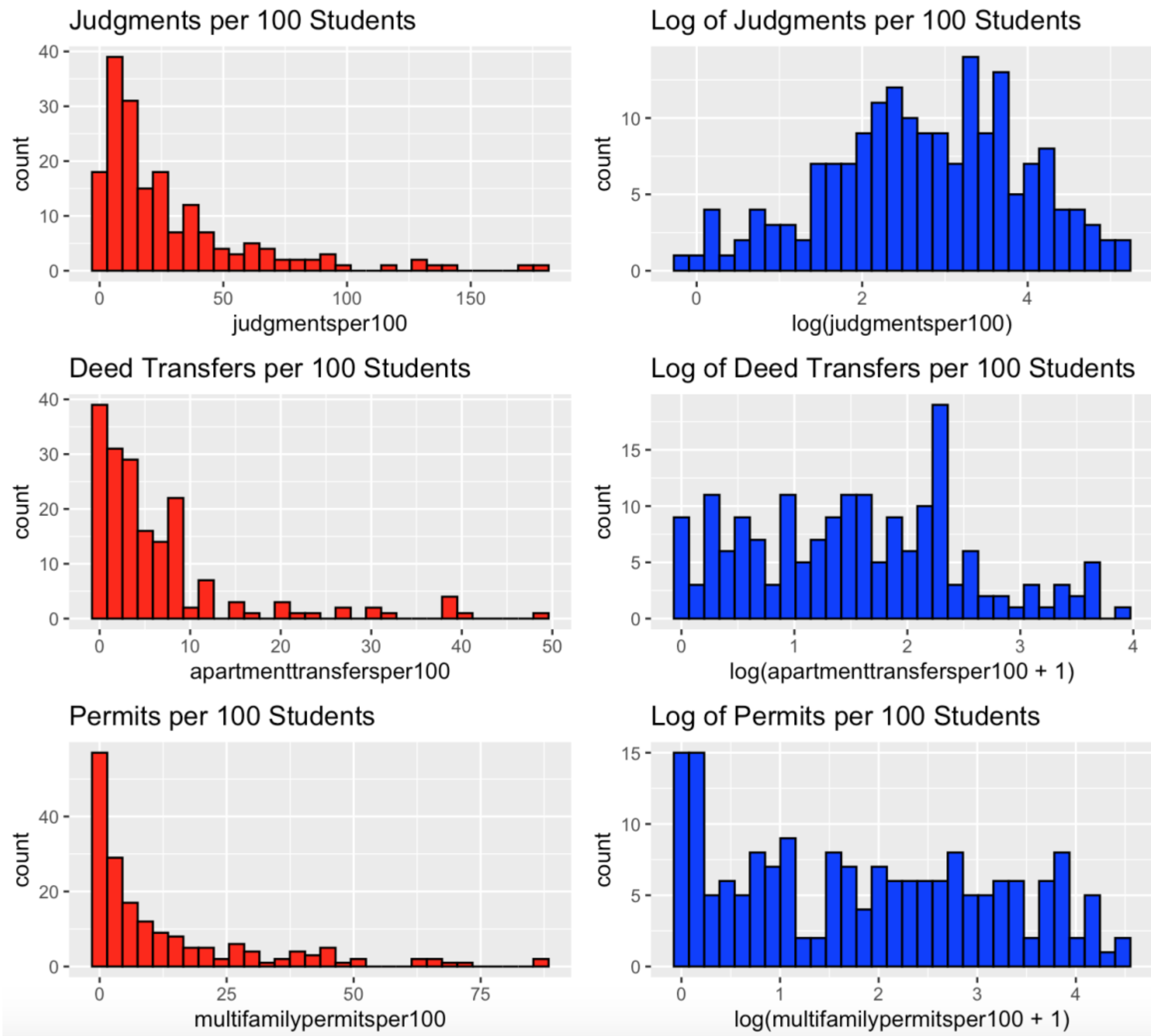
	zone by year (averaged by block group centroids)	

Table 3: Descriptive Statistics of Selected Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Exits	180	130.6	70.8	27	79.8	171.5	435
Exits per 100 Students	180	20.2	5.8	5.2	16.4	24.3	35.9
Judgments	180	207.2	291.1	4	34	250	1,481
Judgments per 100 Students	180	28.4	32.4	0.9	7.4	38.4	179.3
Filings	180	769.4	893.1	14	223.5	1,034	5,257
Filings per 100 Students	180	102.3	77.9	2.2	45.9	136.8	402.9
Apartment Deed Transfers	180	48.8	71.763	0	5	57.2	354
Apartment Transfers per 100 Students	180	6.6	8.8	0	1.2	8.4	48.7
Multifamily Permits	180	117.9	207.9	0	4	140.5	1,076
Multifamily Permits per 100 Students	180	13.3	18.3	0.000	0.9	18.0	86.9
Percent Renter Occupied	180	50.6	10.5	23.9	43.8	57.5	77.7
Median Household Income	180	66,995.6	27,321.1	24,602.4	50,596.8	78,880.1	139,142.4
Percent Black	180	54.2	23.7	8.9	38.6	63.1	96.9
Percent Aged 5-19	180	17.7	2.9	9.9	15.5	19.7	25.2

The variation in the dataset reflects Atlanta's socioeconomic and racial inequality and the extent to which housing insecurity and development activity drive that inequality. This variation will be discussed farther along with the regression results, but also bears mentioning here as it exposes an obstacle to the creation of unbiased statistical models in a city with such extreme gaps. These gaps deserve careful examination in order to better understand their causes and effects, but that examination can only be conducted after controlling for potential outliers that could inhibit statistical analysis. To control for potentially skewing effects, I calculated all independent variables as a ratio per 100 students and log transformed them so that they were more normally distributed (Figure 1). I also log transformed student exits for ease of comparison of regression coefficients

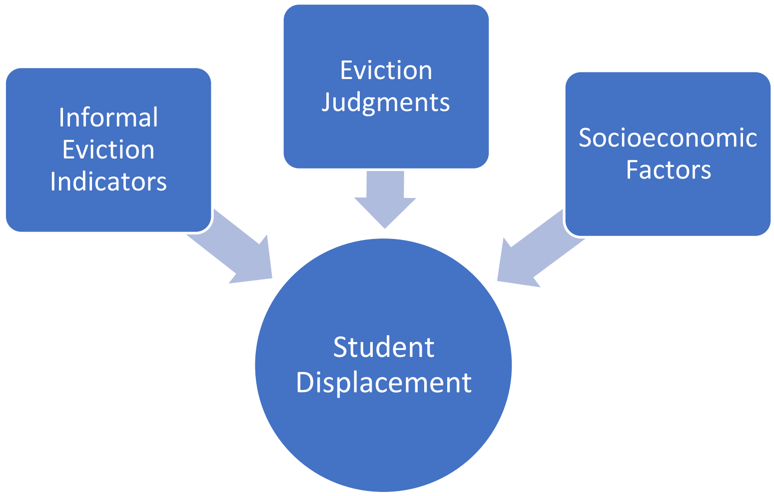
Figure 2: Independent Variables Before and After Transformation



Model Selection and Specification

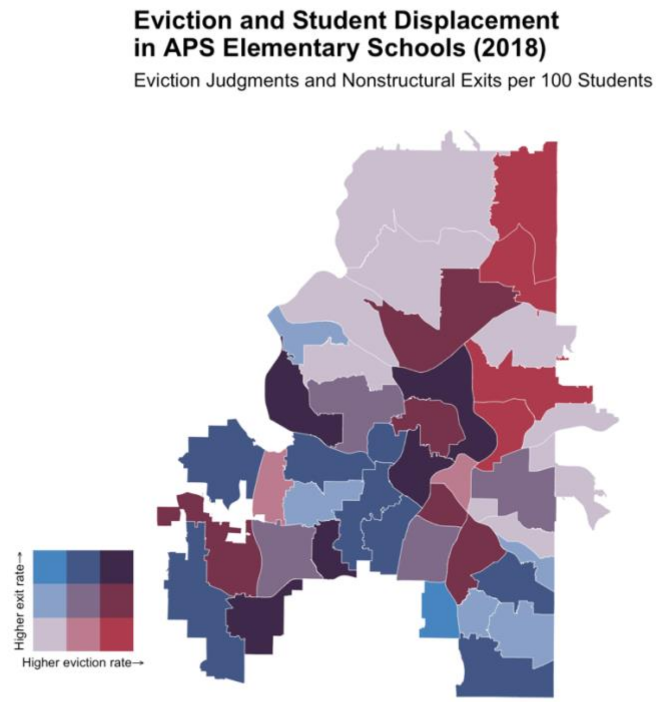
Figure 3 shows the general approach that guided the model selection and construction process. I use a fixed effect panel to estimate these relationships. The panel data model incorporates both cross-sectional and longitudinal data. This two-dimensional structure offers more degrees of freedom with reduced multicollinearity compared with data that is solely cross-sectional or longitudinal (Hsiao, 2005). Panels can minimize the impact of omitted variables by controlling for marginal effects, allow for the identification of relationships between observations across time, and produce more robust estimates of individual of outcomes through the pooling of data (Croissant and Millo (2008), published in the *Journal of Statistical Software*).

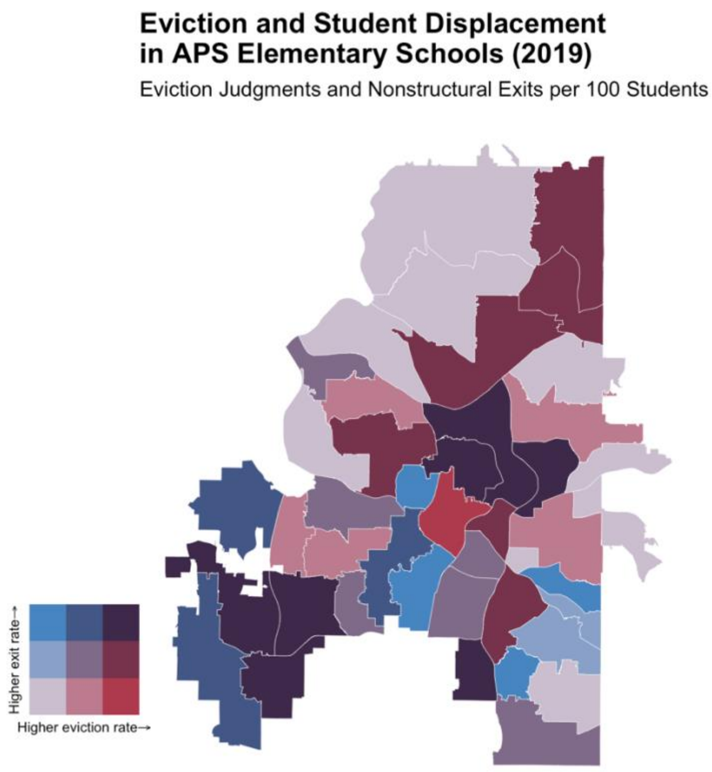
Figure 3: Model of Variable Relationships



Much of panel regression depends on how the model treats unobserved explanatory variables that are correlated with the observed explanatory variables. In fixed effects approaches, the individual-specific variation in y is treated as a random variable that is correlated with the explanatory variables, while in random effects approaches the two are assumed to be uncorrelated (Andrew, Fairbrother, and Jones, 2018). There are many different definitions of the two approaches that vary across disciplines, but, for the purposes of this study, fixed effects models estimate the within group effects of increases over time by controlling for unobserved effects across groups in order to limit omitted variable bias while random effects are holding the within-group effect constant while considering effects across groups to be random (Wooldridge, 2005). I am interested in the relationship between exits and eviction within individual attendance zones as well as how the interaction between the two varies across attendance zones these attendance zones. For this reason, I developed my model to control for fixed effects while also estimating random effects for additional context. Figure 4 shows the spatial distribution of eviction judgments and student exits for elementary school attendance zones in APS for the 2017-2018 and 2018-2019 FTE reporting periods.

Figure 4: Judgments and Student Exits in APS





The two maps show a clear spatial relationship between eviction judgments and student exits and that areas with high rates of both evictions and student exits are primarily located in central and northeast Atlanta around the Atlanta BeltLine as well as in Southwest Atlanta. The use of a fixed effects panel can model the exact nature of this relationship while also indicating if the relationship changes longitudinally. Fixed effects control for any unobserved variables that are associated with explanatory variables and do not vary over time. In order to control for the time-variant factors associated with eviction, I included vectors of covariates in the model. The time dimension consists of 3 FTE reporting periods and with a total n of 60 schools measured 3 times each. I initially used the start and end dates for the 2017-2018 and 2018-2019 school years to filter my count variables before joining them in attendance zones. This approach left me with only two time periods, though, and I adjusted my model to include three 1-year periods corresponding with the submission dates for the three FTE counts that I could access (Table 4).

Table 4: Time Dimension of Panel

Time Dimension	Start Date	End Date	Assigned Value
1	October 5th, 2016	October 3rd, 2017	2017
2	October 4th, 2017	October 2nd, 2018	2018
3	October 3rd, 2018	October 1st, 2019	2019

The model is expressed in the following equation-

$$\log(Y_{it}) = \alpha_i + \log(\beta_{1it}) + \log(\beta_{2it}) + 1\log(\beta_{3it}) + \theta Z_{it} + \mu_{it}$$

where -

Y_{it} represents the change in student exits for school *i* at time *t* for either the entire school population or for a subgroup of students.

α_i is the unknown intercept for each school

β_1 equals the average percent change in student exits associated with a 1% change in eviction judgments, across attendance zones and years.

β_2 equals the average percent change in student exits associated with a 1% change in apartment deed transfers, across attendance zones and years.

β_1 equals the average percent change in student exits associated with a 1% change in multi-family building permits, across attendance zones and years.

θZ_{it} is a vector of time-variant attendance zone-level demographic covariates.

μ_{it} is the random error in the estimated change in school exits for school *i* at time *t*.

To determine the appropriateness of a fixed effects versus a random effects approach, I performed a Hausman-Taylor test with a null hypothesis of no correlation between unique errors and explanatory models. A rejection of the null supports the use of random effects as fixed effects assume there exists such a correlation. The results supported the alternative hypothesis of using fixed effects. I elected to still include a random and mixed methods approach, however, to provide additional context to the results. While the primary goal of this study is to estimate causal impact of changes in the rate of eviction judgments on student exits, I also hope to identify differences between attendance that might be associated with differences in student mobility. Including results from both models allows for causal inferences about the relationship between eviction judgments and student exits via effects while also accounting for the role of variation across APS attendance zones.

Results

Regression Outcome

Before discussing the results of the regression, I would first like to return to the descriptive statistics shown in Table 3. These statistics show that Atlanta is still very much racially and economically segregated and has highly uneven patterns of development. The extremely wide ranges and large standard deviations for student exits, eviction filings, and eviction judgments reflect Atlanta's disparities in housing security and access to equitable learning opportunities. While the overall city eviction rate is high, it clearly does not affect all public school attendance zones equally. Even after normalizing these variables as ratios, the disparities are significant and demonstrate profound differences in residential and educational stability. This instability is likely exacerbated by the huge differences in levels of permit and deed transfer activity. There is significant development activity, but it is heavily concentrated in certain areas. This can result in a housing stock that lacks both affordability and variety, which may partially explain the wide range in rental occupancy rates as well as black population share. Lack of housing options makes evictions more impactful by limiting tenants' options. In a city where poverty is so closely tied to race, the affordability gap created by uneven development patterns threatens to both preserve and deepen racial segregation.

The results of the regression model find a significant causal relationship between eviction judgments and student exits. Table 4 shows the results of both a one- and two-way fixed effects approach. One-way, or "individual", fixed effects estimates only the within-individual effects while holding time effects constant. The two-way approach also includes the individual as well as time-specific effects. Eviction judgments per 100 students was statistically significant at the 99.9% confidence interval for one-way the and at the 95% confidence interval for two-way model. As this is a log-level model, we interpret the coefficients as having a percent relationship. We can use the averages of the variables in the dataset to illustrate this relationship. If we compared an average neighborhood to one where eviction rates are higher by 86 per 100 students, we would expect that neighborhood to have about 5 more exits per 100 students according to the one-way model. The two-way model estimates that that neighborhood would have only need to have 40 more judgments per 100 students to have the same effect. Black population share was also significant at the 95% confidence interval for both models while median household income was significant at the 90% confidence interval. Neither of the estimator variables for informal evictions were significant, with multifamily building permits displaying a small but negative coefficient

Table 4: Estimating the Individual and Time Effects

	Dependent variable:	
	Student Exits	
	Fixed Effects (One-Way)	Fixed Effects (Two-Way)
	(1)	(2)
Eviction Judgments	0.058***	0.124**
	(0.017)	(0.060)
Apartment Deed Transfers	0.027	0.047
	(0.046)	(0.047)
Multifamily Building Permits	-0.022	-0.008
	(0.023)	(0.025)
Renter Occupancy Rate	-0.0003	0.001
	(0.002)	(0.002)
Median Household Income	0.00000*	0.00000**
	(0.00000)	(0.00000)
Black Population Share	0.003***	0.004***
	(0.001)	(0.001)

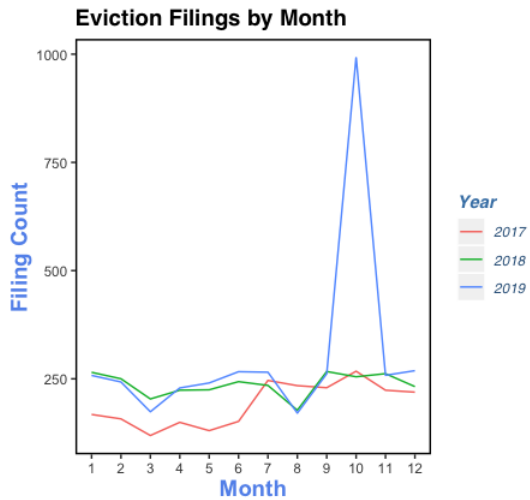
Population Aged 5-19	-0.002	-0.002
	(0.004)	(0.004)
Observations	180	180
R^2	0.138	0.116
Adjusted R^2	-0.365	-0.426
F Statistic	2.587** (df = 7; 113)	2.081* (df = 7; 111)
Note:		*p**p***p<0.01
	All Variables Expressed as Ratio of 100 Students and Log Transformed	

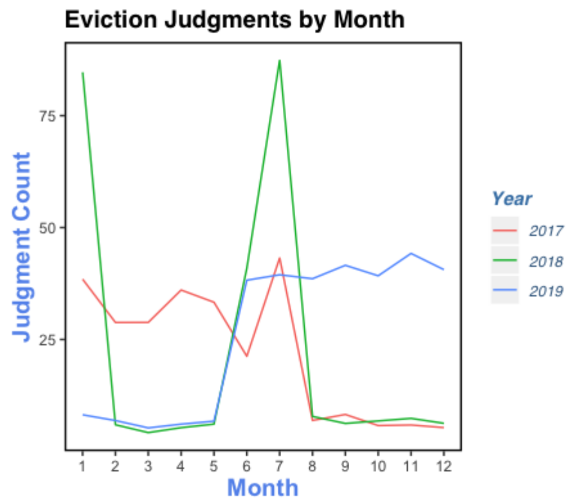
Discussion

Inferences From Results

The difference between the eviction rate coefficients in the two models is significant and warrants an examination of any differences between time periods that may explain it . Because of the small *t* in the panel, variation in one time period could have a significant impact on the outcome of the model. To identify potential anomalies in any one year, I plotted the variation of both eviction judgments and filings across each of the three years in the panel (Figure 4). The 2018-2019 time period had a major spike in filings right before FTE counts were taken while the 2017-2018 time period had a highly volatile eviction rate that spiked in at the beginning of the year and during the summer. Figuring out the causes for these irregularities could be the subject of an entirely different paper, but it seems likely that a change in property ownership, a judicial rotation, or the movement of a backlog of cases to the front of the docket could account for the differences. It also seems like these could be spikes caused by the type of serial filing discussed earlier in the paper. It is unclear whether the time effects will provide more accurate modeling or function as noise in the data that must be controlled.

Figure 4: Time Series Plots of Key Variables





When considering the magnitude of the eviction rate coefficients, it is important to note that this model is estimating the relationship of all evictions of any type on student mobility, rather than only those that affected families with children in public schools. The fact that there is still a significant relationship suggests that more precise data would reveal an even larger correlation. High levels of eviction judgments, regardless of whether they directly impact families with children, predict increases in student mobility in the attendance zones in which they occur. It also bears repeating that all student exits that could be identified as structural or school-initiated were excluded. Higher eviction rates are associated with the nonstructural evictions that consist of both voluntary and involuntary residential moves. Many of the reasons for student exits were coded as "Unknown", and access to more thoroughly documented student exit data is essential to advance to draw stronger causal inferences. This paper has established a relationship between eviction rates and student displacement with the hope that future research while identify the specific dimensions of this relationship.

The application of the results to Kimberly Elementary's attendance zone provides useful context about the size of eviction's impact. Kimberly was the attendance zone with the highest student exit rate in the panel and is located in a low-income, predominantly black area of Atlanta. Between 2017-2018 and 2018-2019, Kimberly's eviction rate per 100 students rose from 5.5 to 26.1. If this pattern were to continue, we would expect Kimberly's rate of exits per 100 students to jump from 36 to 46 the following year.

Implications for Research

In order for these types of predictions to move beyond the abstract, researchers will have to deepen their understanding of the eviction's volatility. The areas with higher levels of eviction still display significant fluctuation across months and years. As the body of eviction research related to the impact of different types of development activity continues to grow, investigators must make an effort to connect that activity to student displacement. While multifamily permits and apartment deed transfers were not significant in this model, they were highly concentrated in some attendance zones and nearly nonexistent in others. The creation of a more detailed dataset spread over more time periods may still be able to identify these factors or others as effective estimators of informal eviction.

More detailed data related to student mobility would also allow for the measurement of individual students and families who experience school disruption as a result of eviction. By developing a level of understanding with local educational agencies that allow for the sharing of student addresses and school registration history, researchers can match school data with parcel level eviction records and model the spatial patterns of student mobility at a much deeper level. Such an effort should also seek to track eviction patterns at multifamily properties with large populations of public school students.

Policy Implications

The advancement of this research has important policy implications for both the affordable housing and public education fields. Although many urban districts have made increased efforts to provide wraparound services to students and families, limited resources still impede the ability of schools to address the structural issues affecting their students. Affordability housing developers and advocates should leverage their existing capacity to bring social and legal aid workers to all vulnerable schools. While some landlords habitually use eviction as a tool to coerce payment and compliance from tenants, others would welcome the increased residential stability provided by strong local schools. Efforts to increase tenant protections and provide legal defense in eviction court should also incorporate the student-level impact into their messaging and lobbying. Increasing protections against discriminating against tenants with children would have the dual effect of reducing family vulnerability to eviction and lowering rates of student turnover.

School advocated must also push for districts to have greater autonomy over how they use their surplus property. Restrictions on what purposes this property can be used for and how it can be sold or transferred limit the ability of schools to potentially add to their local affordable housing stock. High and rising mobility rates also call for better information sharing within and across districts. It is far too easy for a student to change schools multiple times within one school year without anyone intervening, and greater alignment of student information systems would facilitate earlier identification of the most vulnerable students.

The results of this study show that there is a clear relationship between evictions and student exits both within and between attendance zones. Eviction judgments predict increases in exits within attendance zones and attendance zones with higher rates are more likely to have more student displacement. Atlanta's eviction rates continue to rank among the highest in the nation, and recognition that its impact extends beyond the urban rental housing market is necessary to begin creating real policy solutions. At the same time, the erosion of the resources and stability of urban public schools limits intergenerational mobility and accelerates already widening inequality. I hope that future research will look at this issue across multiple school districts and housing markets at an individual or parcel level. There is great potential for a collaborative effort to utilize full state enrollment reports in conjunction with eviction case records to assemble a unique dataset. The findings produced by this study with fairly limited scope and access demonstrate what can be accomplished when researchers probe the intersection of housing and education.

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