

The Impact of the Great Recession on Student Achievement: Evidence from Population Data

AUTHORS

Kenneth Shores

University of Pennsylvania

Matthew P. Steinberg

University of Pennsylvania

ABSTRACT

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The Impact of the Great Recession on Student Achievement: *Evidence from Population Data*

Kenneth Shores
Matthew P. Steinberg

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Abstract

The Great Recession was the most severe economic downturn in the United States since the Great Depression. Using newly available population-level achievement data from the Stanford Education Data Archive (SEDA), we estimate the impact of the Great Recession on the math and English language arts (ELA) achievement of all grade 3-8 students in the United States. Employing a difference-in-differences strategy that leverages both cross-district variation in the economic shock of the recession and within-district, cross-cohort variation in school-age years of exposure to the recession, we find that the onset of the Great Recession significantly reduced student math and ELA achievement. Moreover, the recessionary effect on student achievement was concentrated among school districts serving more economically disadvantaged and minority students, indicating that the adverse effects of the recession were not distributed equally among the population of U.S. students. We also find that the academic impact of the recession was more severe for students who were older at the time of first exposure to the recession, compared to their younger counterparts. Finally, the recession's effects on student achievement were concentrated in districts with the largest reductions in teacher personnel, providing evidence that the effects we observe are driven, in part, by the recession's negative effects on school resources. We discuss the implications of and potential policy responses to economic shocks that adversely affect student achievement and widen educational inequality.

Keywords: Great Recession; economic downturn; student achievement

JEL codes: I21, I25

Introduction

December 2007 marked the onset of an 18-month economic recession that had severe and wide-ranging economic and educational consequences. During this period, now referred to as the Great Recession, the unemployment rate rose by 5 percentage points, reaching 10 percent by October 2009 (Evans, Schwab & Wager, 2017). In the wake of the Great Recession, the U.S. housing market declined dramatically and household wealth suffered under an unprecedented shock to equity markets (Hurd & Rohwedder, 2010; Wolff et al., 2011). While states and counties with the largest shares of construction employment and inflated housing stock were hardest hit by the Great Recession (Fogli, Hill & Perri, 2015), its disproportionate effect also varied along ethnic lines. Indeed, the white-black and white-Hispanic wealth gaps increased between 2007 to 2013 (Kochhar & Fry, 2014).

The effect of the Great Recession on school districts was similarly pronounced, imposing constraints on state and local funding for schools (Business Cycle Dating Committee, 2010; Chakrabarti & Livingston, 2013; Leachman & Mai, 2014). Evans and colleagues (2017) estimate that the recession reduced state and local revenues by 5 percent, and that educational revenues did not recover to pre-recession levels until nearly five years after the recession. These fiscal shocks led to subsequent reductions in educational employment, with public school employment falling by 3.7 percent, a loss of approximately 300,000 jobs nationwide (Evans, Schwab and Wager, 2017).

The educational impact of the Great Recession was also disproportionately distributed. Evans, Schwab and Wager (2017) find that inequality in school spending – the spending gap between resource rich and poor school districts – rose throughout the period, attributable, in part, to differences in the ways schools are funded. For example, revenues declined at greater rates

among districts that relied more heavily on state aid; such districts tend to serve a more economically disadvantaged student population. In light of the fact that many local districts raised property taxes in response to the fiscal shock of declining housing values (Chakrabarti et al., 2014; Evans, Schwab and Wager, 2017), property tax increases during economic recessions will disproportionately affect residents of school districts serving students from more economically struggling households.

Given that parental unemployment and negative shocks to household income and school spending adversely affect student achievement outcomes (Ananat, et al., 2011; Dahl & Lochner, 2012; Jackson, Johnson and Persico, 2016; Lafortune, Rothstein & Schanzenbach, 2017; Stevens & Schaller, 2011), the onset of the Great Recession may also have negatively affected student achievement. Though recent evidence indicates that inequality in school spending rose during the Great Recession (Evans, Schwab and Wager, 2017), it is yet unknown whether (and to what extent) the onset of the Great Recession impacted student achievement. Moreover, no evidence yet exists on whether the Great Recession exacerbated the inequality of student achievement outcomes across school districts serving different student populations (e.g., by socioeconomic status and race/ethnicity).

To fill the gap in our understanding of the recessionary impacts of the Great Recession, we examine the academic consequences of the Great Recession across all U.S. school districts, addressing the following questions: (1) Did exposure to the recession affect student achievement? (2) Did exposure to the recession affect student achievement differently depending on the age of first exposure? (3) Did exposure to the recession disproportionately affect student achievement in districts serving higher concentrations of low-income and minority students?

To address these questions, we first employ time-varying county-level unemployment data to construct a recession intensity index (Yagan, 2016). This index measures the extent of cross-county variation in the magnitude of the economic shock due to the Great Recession. Next, we leverage a unique dataset recently made available through the Stanford Education Data Archive (SEDA). SEDA provides population-level achievement data for all tested students in grades 3-8 in the United States in the years during and after the Great Recession (i.e., 2008-09 through 2012-13 school years). Using these data, we implement a difference-in-differences (DD) strategy to estimate the impact of exposure to the Great Recession on the math and English language arts (ELA) achievement of all grade 3-8 students in the United States.

Our DD strategy makes use of the joint facts that: (a) the economic shock of the recession varied across districts; and (b) students in different cohorts within the same school district varied in the number of school-age years they were exposed to the recession. First, students in the same cohort but located in different districts likely experienced different educational outcomes due to the intensity of the recession in their local settings. Second, additional years of cumulative exposure to economic hardship are likely to decrease academic achievement. Taken together, the recessionary impact on student achievement was likely greatest for those students with more years of exposure to the recession and who were in districts most adversely affected by the economic downturn.

We find that an additional year of exposure to the Great Recession reduced student ELA and math achievement by an average of 0.02 and 0.03 standard deviations, respectively. The adverse effect of the Great Recession on student achievement was most severe for students who first experienced the recession in grades 5-7, relative to younger students who first experienced the recession in kindergarten and first grade. Further, the effect of the recession was concentrated

among school districts serving more economically disadvantaged students. In districts with the highest proportion of students qualifying for free or reduced-price lunch (FRPL) and in districts with the highest proportion of black students, the recession reduced math achievement by 0.05 standard deviations. In comparison, we find no significant recessionary effect in districts with relatively few FRPL or black students. As a result, the recession exacerbated achievement inequalities between poor and more economically advantaged school districts. Finally, the recession's effects on student achievement were concentrated in districts with the largest reductions in teacher personnel, providing evidence that the effects we observe are driven, in part, by the recession's negative effects on school resources.

The paper proceeds as follows. In the next section, we describe our approach for measuring district-level variation in the intensity of the Great Recession. Next, we detail the district-level data and the empirical strategy for identifying the impact of the Great Recession on student achievement. We then present our results, and conclude by discussing the implications of and potential policy responses to economic shocks that adversely affect student achievement and widen educational inequality.

Measuring Recession Intensity

We measure the intensity of the Great Recession using average annual county-level total employment data from the Quarterly Census of Employment and Wages (QCEW).¹ Following Yagan (2016), we construct the following index of recession intensity:

$$(1) \text{Recession}_c = \left[\ln \left(\frac{E_{c,2010}}{E_{c,2007}} \right) - \ln \left(\frac{E_{c,2006}}{E_{c,2003}} \right) \right] - \left[\ln \left(\frac{E_{agg,2010}}{E_{agg,2007}} \right) - \ln \left(\frac{E_{agg,2006}}{E_{c,2003}} \right) \right]$$

¹ The QCEW program publishes a quarterly count of employment and wages reported by employers covering 98 percent of U.S. jobs, available at the county, MSA, state and national levels by industry. Average annual data were downloaded from the Bureau of Labor Statistics for each county and year from https://data.bls.gov/cew/apps/data_views/.

where E_{ct} denotes the number of employed workers in county c in the Spring of academic year t ,² and where agg denotes total employment across the continental U.S. in year t .³ Each county's recession intensity is measured as the change in log employment during the recessionary period (Spring 2007 to Spring 2010, or fiscal years 2006 to 2009) relative to the county's pre-recession trend (Spring 2003 to Spring 2006).⁴ The county-specific measure of recession intensity is then normalized by subtracting the aggregate employment trend. For ease of interpretation, we convert the continuous measure of $Recession_c$ into four quartiles.⁵

To examine whether the variable $Recession_c$ captures changes across a range of economic indicators, we first plot the average unemployment rate by recession intensity quartile (see Figure 1).⁶ Figure 1 confirms that the measure of recession intensity captures meaningful geographic variation in unemployment trends beginning in Spring 2008. Note that the pre-recession unemployment trends for each of the intensity quartiles are nearly identical, both in

² For example, the Spring academic year 2010 corresponds to the academic year 2009-2010, which in turn corresponds to fiscal year 2009. Years are indexed in Spring academic years to correspond to the student achievement data used below.

³ Note that the variable $Recession_c$ will contain multiple districts d for every county c , as there are 3,051 counties in the continental U.S. for which we have achievement and employment data and approximately 11,900 school districts (depending on whether the subject is English/Language Arts (ELA) or math). The regression equation, described below, will include the subscript d for this reason, but recession intensity varies only across counties c .

⁴ Yagan (2016) uses the pre-recession period of 2001 to 2004 (fiscal years 2000 to 2003) because (a) 2001 is the earliest year in which county-level employment data are available and (b) the years following Spring 2004 include the inflated bubble years that immediately precede the U.S. recession. For our purposes, we are interested in capturing changes in recession intensity as proximal to the observed achievement data as possible. Moreover, a 2001 base period overlaps with the previous US recession. In a series of sensitivity analyses, we show that our main results (which are based on the 2003-2006 pre-recession period) are qualitatively the same as when the pre-recession period is defined as in Yagan (2016).

⁵ Because $Recession$ is measured at the county level and because the number of districts (and students in grades 3 through 8) are not uniformly distributed within county, the number of counties will be approximately uniformly distributed across the four quartiles but the number of districts/students will not be. For this reason, we also construct weighted quartiles in which the weights include either district counts (the number of districts in a county) or enrollment counts (the number of students enrolled in grades 3 through 8 in a county). As discussed below, results are insensitive to the way in which quartiles are constructed.

⁶ We retrieved the unemployment rate from the Local Area Unemployment Statistics (LAUS) annual averages for each county, available for download at the Bureau of Labor Statistics here <https://www.bls.gov/lau/#cntyaa>.

levels and in trends. Only in the post-recession period do we observe a divergence in unemployment trends by recession intensity quartile.⁷

<Figure 1 about here>

To provide additional evidence that the recession intensity index ($Recession_c$) captures meaningful variation across a broad range of economic indicators, Table 1 displays pre- and during-recession averages for the following economic variables: (i) unemployment rate; (ii) real per capita unemployment insurance; (iii) the percentage of children in poverty; (iv) real household earnings; and (v) real per capita income.⁸ We construct averages for each of these indicators for Spring academic years 2003 to 2006 (pre-recession period) and 2007 to 2010 (during-recession period) for the entire analytic sample and by recession intensity quartile.⁹ All finance data are inflated using the CPI and are placed in \$2013.¹⁰

<Table 1 about here>

As has been previously documented, economic conditions worsened following the onset of the Great Recession (Grusky, et al., 2011; Hurd & Rohwedder, 2010; Yagan, 2016). Indeed,

⁷ In Figure A1 we reproduce Figure 1 using the alternative pre-recession period of Spring 2001 to Spring 2004. Figure A1 demonstrates a similar overall pattern: the divergence in unemployment trends, by recession intensity quartile, following Spring 2007; however, the pre-recession period is less aligned in the pre-recession period and the magnitude of the difference in the unemployment rate across recession intensity quartiles is smaller in magnitude (and less monotonic).

⁸ Per capita unemployment insurance, per capita earnings and per capita income are available from the Bureau of Economic Analysis (BEA) regional economic accounts. Local area economic profiles are available at the county level for variables such as unemployment insurance, earnings and income. Data were downloaded here <https://www.bea.gov/regional/downloadzip.cfm>. The proportion of children in poverty is available from the Small Area Income and Poverty Estimates (SAIPE) and are available for school districts and counties. SAIPE data are intended to provide model-based estimates of income and poverty statistics, based on data from administrative and census records. County-level data were downloaded at <https://www.census.gov/did/www/saipe/data/staecounty/data/index.html>.

⁹ For example, 0.067 is the mean unemployment rate over the recessionary period (Spring 2007 through Spring 2010) for counties in quartile four of the recession intensity quartile.

¹⁰ Figure A2 displays a map of the continental United States and overlays $Recession_c$, which we standardize ($\sim N(0,1)$) and rescale so that higher values indicate more adverse economic shocks due to the recession (i.e., greater employment loss, as measured by negative log employment growth). Figure A2 shows that while there was some regional concentration of the recessionary impact, employment shocks were generally widespread across the U.S. Yagan (2016) shows a similar pattern using commuting zones.

from the pre-recession period (fiscal years 2002 to 2005) to the period during the recession (fiscal years 2006 to 2009), we observe increases in the unemployment rate, unemployment insurance, and the childhood poverty rate, and declines in household earnings and per capita income (see Table 1, *Analytic Sample*). Comparing recession intensity quartiles one and four – i.e., districts that were least and most adversely affected by the economic shock of the recession, respectively – the change in economic conditions is larger for each of the economic variables in recession intensity quartile four than in recession intensity quartile one. These results further indicate that the recession intensity quartiles, which we construct using the relatively parsimonious measure of net log employment changes, capture meaningful variation across quartiles for a broad range of economic indicators.

Based on our findings in Table 1, students living in districts more adversely affected by the recession faced more severe economic conditions (at home and at school) than students whose communities were relatively unaffected by the shock of the Great Recession. We next describe the data and methods used to assess whether students who experienced worse economic conditions due to the recession also realized worse academic achievement outcomes, compared to students living in districts that were less severely impacted by the recession.

Data & Sample

We construct a district-level panel dataset consisting of the population of public-school districts in the United States for the 2008-09 through 2012-13 school years. To do so, we combine data from multiple sources, including achievement information from the Stanford Education Data Archive (SEDA) and demographic, revenue and expenditure information from the U.S. Department of Education's Common Core of Data (CCD). We describe each data source and accompanying variables below.

The SEDA data include over 200 million standardized achievement test scores for approximately 40 million public school students in grades 3 through 8 during the 2008-09 through 2012-13 school years.¹¹ Achievement data are estimated from state accountability “coarsened” proficiency data (percents or counts of students falling into different proficiency categories, such as “Basic,” “Proficient” and “Advanced”, which are the most commonly reported statistic available from state accountability systems), as described by Reardon et al. (2017). Using a heteroskedastic ordered probit model, Reardon and colleagues show that means and standard deviations from ordered proficiency data can be recovered with little bias.

To make these test scores comparable across states (which, in almost all cases, use different standardized assessments) and across time, the achievement data are placed on a common scale using the National Assessment of Educational Progress (the state NAEP). This linking procedure has been described by Reardon, Kalogrides and Ho (2017). The NAEP is a useful benchmarking tool, as it has remained relatively unchanged over time and is the same test for each state. Thus, as Reardon, Kalogrides and Ho (2017) show, it is possible to equate the NAEP mean and standard deviation to the distribution of district-level achievement data estimated from state-specific standardized assessments. The SEDA data therefore provide a unique opportunity to evaluate large-scale changes in the education production function, as they allow for both within and between state comparisons of academic achievement over time. We use district-by-year-by-grade (i.e., district-by-cohort) achievement scores, which are

¹¹ The 200 million test scores are for 40 million students across ten cohorts and five school years (2008-09 through 2012-13). Each U.S. age cohort consists of approximately four million students.

standardized (mean zero, standard deviation one) for both math and ELA, as the outcome variables of interest.¹²

We supplement the SEDA achievement data with annual, district-level demographic data from the Common Core of Data (CCD) and resource data from the CCD Local Education Agency Finance Survey (F-33). Demographic information includes total K-12 enrollment, total enrollment for grades 3-8, class size (total K-12 enrollment per teacher), proportions of grades 3-8 students that are Asian, black, Hispanic, and white, proportions of K-12 students qualifying for free (or reduced) price lunch (FRPL).¹³ District resource information includes real per pupil total revenues and real per pupil instructional expenditures (inflated using the 2013 CPI). Finally, in cases where district locales change over time, we include indicator variables for whether the district is urban, suburban, town or rural, which are available from the CCD.

Sample

Our analytic sample includes 11,748 school districts in the United States, which include 95.6 percent of publicly enrolled (both traditional and charter school) students in grades 3 through 8 for years 2008-09 through 2012-13.¹⁴ The analytic sample includes districts that are

¹² Data are standardized relative to a particular cohort c^* , specifically the median cohort in the available SEDA data, allowing for cross-cohort comparisons of achievement differences. Let $\hat{u}_{dyg}^{c^*}$ represent standardized achievement in district d , year y and grade g , and cohort c^* represent any specific cohort, where a cohort is defined by its year minus grade. Then, the data are demeaned by $(\hat{u}_{dyg}^{naep} - \hat{u}_{(yg)^*}^{naep})$, where \hat{u}_{dyg}^{naep} is the unstandardized district achievement and $\hat{u}_{(c)^*}^{naep}$ is mean achievement for cohort c^* from the population NAEP data. The demeaned data are then divided by $\hat{\sigma}_{c^*}^{naep}$, which is the population standard deviation for cohort c^* . See Reardon, Kalogrides and Ho (2017) for additional details. Additional technical documentation is available for download here: https://cepa.stanford.edu/sites/default/files/SEDA%20Technical%20Documentation%20Version1_1.pdf

¹³ District demographic data for students qualifying for Individual Education Plans (IEP, or special education) and those who are English Language Learners (ELL) are available in 2007-2008, which are used to construct quartiles to estimate heterogeneous effects (see below). Due to missing data, these variables are not included as time-varying characteristics.

¹⁴ Charter schools and schools administered by the state have a unique local education agency ID number (LEAID) but operate inside a geographic boundary assigned a different LEAID. For example, finance data for traditional public schools in New York City are assigned an LEAID of 3620580, but charter districts operating inside New York City are assigned unique LEAID numbers depending on the charter agency. Because Census and economic data are assigned to geographic areas and not to charter agencies, charter districts are reassigned the LEAID number

not missing ELA achievement, demographic information (including FRPL and racial composition), and expenditure data for the 2008-09 through 2012-13 school years. Further, the analytic sample includes district that can be linked to county-level employment data in the appropriate years to generate a recession intensity value.¹⁵

Table 2 presents descriptive statistics for the additional control variables described above. Data are shown for the 2008-09 through 2012-13 school years. For time-varying district characteristics, data are averaged across grades (3 through 8) and years, for the full analytic sample as well as by recession intensity quartile.

<Table 2 about here>

Table 3 presents descriptive statistics for the achievement data in our analytic sample. Data are shown for the 2008-09 to 2012-13 school years and are averaged across grades 3 through 8, for the full analytic sample as well as by recession intensity quartile. Mean math and ELA achievement are precision-weighted using the inverse of the estimated standard error squared ($1/\hat{\sigma}^2$). The use of precision-weighting is motivated by the fact that the estimated standard errors for district means are, in many cases, a multiple of the estimated mean. For example, of the 315,034 ELA district-year-grade observations available, 11,652 of those have standard errors greater than or equal to the estimated mean. Precision-weighting discounts these

that corresponds to the geographic boundary. These geographic boundaries are based on the latitude and longitude available in the school-universe file from the CCD. All charter districts are thereby subsumed into the geographic district; thus, the 11,748 school districts in the sample include both charter and traditional public schools. For additional discussion, see the SEDA Technical Documentation available here:

https://cepa.stanford.edu/sites/default/files/SEDA%20Technical%20Documentation%20Version1_1.pdf.

¹⁵ The actual analytic sample will vary slightly depending on whether we estimate a model with ELA or math scores, as there are some districts for which ELA scores are available and math unavailable, or vice-versa. In practice, there are 11,748 districts with non-missing ELA scores (and other variables) and 11,730 districts with non-missing math scores (and other variables). The analytic sample for math achievement provides coverage for 92.2 percent of the publicly enrolled grade 3-8 student population in years 2009-2013. Fewer math scores are available as the SEDA data eliminate state test data if the state allowed students to select into a particular content-specific math exam. This kind of selection occurred, for example, in California in grades 7 and 8, where students could select to take a general math, geometry or algebra exam.

observations. Descriptive statistics and subsequent regression models are weighted in this way, a procedure suggested by Reardon et al. (2016, 2017a, 2017b).

<Table 3 about here>

Empirical Approach

To estimate the effect of the recession on academic achievement, we leverage the fact that cohorts of students (e.g., 5th grade students in the 2008-09 school year) within the same school district varied in their school-age years of exposure to the recession. Specifically, the recessionary impact on student achievement was likely greatest for cohorts – students at the grade*year level – who experienced more years of schooling during the recession. Second, since the economic consequences of the recession varied across districts (i.e., cross-district variation in recession intensity), students in the same cohort but located in different districts likely experienced different educational outcomes due to the intensity of the recession in their local settings. As a result, the recessionary impact on student achievement was likely greatest for students (a) with more years of exposure to the recession and (b) located in districts most adversely affected by the economic downturn. We model both exposure to the recession and the moderating effect of recessionary intensity on student achievement as:

$$(2) Y_{dtg} = \beta_0 + \beta^q \left(\sum_{q=1}^Q \text{Recession}_d^q * \text{Exposure}_{gt} \right) + \mathbf{X}_{dt} \boldsymbol{\nu} + \mathbf{X}_{dtg} \boldsymbol{\gamma} + \delta_d + \theta_t + \lambda_g + \varepsilon_{dtg}$$

where Y_{dtg} is an achievement outcome in district d during school year t for students in grade g . The variable Recession_d^q is the measure of recession intensity for district d (where district d is nested within county c , as described in Equation (1)), which we convert into q quartiles. The variable Exposure is the number of school-age years of exposure to the recession for students in grade g in school year t (and equals 0, 1 or 2). In the SEDA achievement data, ten

cohorts (c) of test scores are available – i.e., ten unique grade (g)*year (t) combinations. Table A1 summarizes how we define the c cohorts, and Table A2 summarizes the cohort-specific years of exposure to the recession. The vector \mathbf{X}_{dt} includes annual district demographic and resource characteristics and \mathbf{X}_{dtg} controls for time- and grade- varying district demographic characteristics. Specifically, the vector \mathbf{X}_{dt} includes class size (total K-12 enrollment per teacher), proportions of K-12 students qualifying for free (or reduced) price lunch, real per pupil total revenues, real per pupil instructional expenditures (inflated using the 2013 CPI), and indicator variables for whether the district is urban, suburban, a town or rural. The vector \mathbf{X}_{dtg} includes the proportions of students in grades 3-8 that are Hispanic, white and black.

We model changes in achievement within districts and across cohorts within the same academic year by including district (δ_d), year (θ_t) and grade (λ_g) fixed effects.¹⁶ Standard errors are clustered at the district level to account for serial correlation (Bertrand, Duflo & Mullainathan, 2004). The parameter β^q maps the effect of exposure to the recession on student achievement across q quantiles of recession intensity, under the identifying assumption that the timing of the recession relative to cohort-specific exposure is random, conditional on district and year effects. This semi-parametric specification allows us to compare the effect of the recession for the same cohorts (within a given school year) across the q quantiles, allowing insight into whether (and the extent to which) the impact of the recession was greater for the same cohort of students located in districts with greater recessionary intensity. The principle DD estimand of interest is $\beta^{(q=4)} - \beta^{(q=1)}$, or the net change in achievement between recession intensity quartile 4 and recession intensity quartile 1. The additional estimands $\beta^{(q=4)} - \beta^{(q=2)}$ and $\beta^{(q=4)} -$

¹⁶ Including grade and year fixed effects is equivalent to including cohort fixed effects, since cohort is a linear combination of grade and school year.

$\beta^{(q=3)}$ are also of interest. Importantly, if our identification strategy is valid, we would expect there to be increasingly large effects on student achievement when comparing across quartiles. Thus, these estimands provide an important verification of our identification strategy; namely, the monotonicity of effects across quartiles of the recession intensity index.

This DD strategy relies on three assumptions. First, that the timing of school-age exposure to the Great Recession, for a cohort of students (e.g., 5th grade students in the 2008-09 school year) within a given school district, was random. This assumption is predicated on plausibly random assignment to birth cohort, such that the onset of the Great Recession was exogenous to the timing of age of school entry. Second, that the intensity of the recessionary shock was not correlated with state- or district-level policy (economic and/or educational) responses that would have impacted student achievement. To address this assumption, we estimate models that include, alternatively, state-by-year and district-by-year fixed effects to account for any state and/or district policy responses that were contemporaneous to the onset of the recession. We later show that our main results are robust to models that include either state-by-year or district-by-year fixed effects, providing evidence that the main DD estimates capture the impact of recessionary exposure and not endogenous state- or district-specific responses to the recession. Third, that the recessionary shock did not induce non-random sorting of students (and families) across school districts. The assumption that sorting is effectively random is plausible given the growing body of empirical research showing that economic shocks (either in the form of trade shocks or recessionary events) are “sticky” in the sense that individuals most affected by these shocks remain in their geographic boundaries (Frey, 2009; Katz, 2010; Autor,

et al., 2016; Yagan, 2016). We also show empirically that there were no substantive demographic changes across districts, by recession intensity, following the onset of the Great Recession.¹⁷

We then examine whether the recessionary effects (if any) varied depending on the grade in which cohorts were first exposed to the recession. In particular, did students who were younger (or older) at the time of the recession, but with equal years of exposure, realize differential effects on their achievement (i.e., was the achievement of younger (or older) students more (or less) resilient to the recession)? To lend insight into this question, we take advantage of the fact that seven (of the ten) cohorts in our analytic sample had equal school-age years of exposure to the recession (and at least two years of test data), but were first exposed to the recession in different grades. For example, the 2003 and 2008 cohorts were each exposed to the recession for two years, but they differ in that the recession began in kindergarten for the 2008 cohort while the recession began in 5th grade for the 2003 cohort.

To examine this, we replace the linear exposure term in equation (2) with cohort indicator variables in the following specification:

$$(3) Y_{dtg} = \beta_0 + \beta_c^q \left(\sum_{q=1}^Q \text{Recession}_d^q * \sum_{c=2002}^{c=2008} \text{Cohort}_c \right) + \mathbf{X}_{dt} \boldsymbol{\nu} + \mathbf{X}_{dtg} \boldsymbol{\gamma} + \delta_d + \theta_t + \lambda_g + \varepsilon_{dtg}$$

In equation (3), each of cohorts 2002 through 2008, inclusive, is entered as an indicator variable. Identification of the cohort-specific effects is identical to model (2), where Cohorts 2001 and 2010 are absorbed by the year effects (as they have only one year of test data) and

¹⁷ An additional assumption implicit in this empirical approach is that achievement in districts with the most severe recessionary shocks were not trending downward in the pre-recession period. While we are unable to test for pre-treatment achievement trend differences across recession intensity quartiles (since 2008-09 is the first year in which SEDA data are available), we do examine whether unit-specific trend differences (during and after the recessionary period) bias estimates of the main effect of the recession on student achievement. Following Angrist & Pischke (2009), we find that our main results are robust to the inclusion of both county-specific linear time trends and district-specific linear time trends (results are available from the authors upon request).

Cohort 2009 is the omitted cohort with multiple years of test data and only one year of exposure. All other variables are defined as in equation (2), and standard errors are clustered at the district level. The parameter β_c^q maps the change in achievement among c cohorts (of which there are seven with two years of exposure to the recession and at least two years of test data) across q quantiles of recession intensity.

This approach allows for two distinct comparisons. First, we compare the recessionary impact on student achievement across cohorts of students, leveraging cross-cohort variation (within districts) to generate a causal estimate of the impact of the timing of exposure to the recession on changes in student achievement. Second, the DD estimand $-Cohort_c \times (\beta^{q=4} - \beta^{q=q^*})$ – provides the recessionary impact on student achievement across recession intensity quartiles q^* for the same cohort c of students.

Finally, we test whether recessionary effects varied by the demographic and racial/ethnic composition of school districts. To do this, we use CCD data from Spring 2008 (the 2007-08 school year) to generate quartiles for the following district-level characteristics: (i) percent of FRPL eligible students; (ii) percent of IEP students; (iii) percent of ELL students; and (iv) racial proportions (i.e., percent of district students that are either black, Hispanic or white), for a total of six heterogeneous variables disaggregated into four quartiles. We also construct urbanicity indicator variables, of which there are four (urban, suburban, town and rural), based on CCD data from Spring 2008. We then interact $\sum_{q=1}^Q Recession_d^q * Exposure_{gt}$ with these demographic quartiles (or urbanicity indicators) to recover recession intensity by demographic or urbanicity effects. This approach also allows for two comparisons: (i) within recession intensity quartile and across demographic/urbanicity variables; and (ii) within demographic/urbanicity variables and across recession intensity quartiles. From these models, we estimate whether the

recession differentially affected districts serving higher (or lower) proportions of minority and low-income students, students requiring additional academic services (i.e., ELL and IEP students), and districts that are more (or less) densely populated.

Results

We begin by describing the impact of the Great Recession on student math and ELA achievement. We then examine the robustness of our main results to alternative constructions of the recession intensity index, potential state and district-level policy responses that may be endogenous to the recession, and non-random student sorting across recession intensity quartiles. Next, we explore heterogeneity of recession effects; first, we discuss whether the recessionary effect on achievement varied by the age in which students were first exposed to the recession; and second, we describe whether the recessionary effect varied by the student composition and geographic location of school districts. We conclude by examining whether recessionary effects on student achievement are mediated by changes in school resources.

Recessionary Effects on Student Achievement

Table 4 summarizes the main effect of the Great Recession on student academic achievement. We find that exposure to the recession negatively affected student achievement; these results are based on the difference-in-differences estimates (see Table 4, DD Estimates, Columns 1 and 3). Students most adversely affected by the recession (i.e., $\beta^{q=4} - \beta^{q=1}$) realized lower math and ELA achievement, on the order of 0.033 and 0.021 standard deviations, respectively, for each additional school-age year of exposure. When recession intensity is treated as a continuous variable,¹⁸ we find that students located in communities where the intensity of the recession was one standard deviation greater, realized, on average, a decline of 0.010 and

¹⁸ Recession intensity is standardized to be mean zero and standard deviation one $\sim N(0,1)$ and labeled RI^{Linear} . Results are shown in Table 4, columns 2 and 4.

0.007 standard deviations in math and ELA achievement, respectively, for each additional school-age year of exposure to the recession (see Table 4, columns 2 and 4).

Notably, the recessionary effect on student achievement is declining across recession intensity quartiles. Indeed, the recessionary effect on student math and ELA achievement is more modest – on the order of 0.015 and 0.011 standard deviations – for students most adversely affected by the recession (quartile 4) compared to students where the intensity of the recession was less severe (i.e., quartile 2), and even smaller – less than 0.01 standard deviations – when compared to students located in districts in quartile 3 of recession intensity. The monotonicity of recessionary effects provides further support for the validity of our identification strategy, and reveals that students located in districts more adversely impacted by the recession suffered more severe achievement losses.

<Table 4 about here>

Sensitivity Analyses

We next explore whether the main effects of the recession on student achievement are sensitive to: (a) the construction of recession intensity quartiles (i.e., defining treatment); (b) endogenous state- and district-specific policy responses that may be correlated with student achievement; and (c) non-random student sorting across recession intensity quartiles.

First, we construct an alternative recession intensity index in which the pre-recession period includes fiscal years 2000-2003 (Spring 2001 to Spring 2004), as in Yagan (2016); this compares to our principle construction of recession intensity based on a pre-recession period including fiscal years 2002-2005 (Spring 2003 to Spring 2006). Notably, by Spring 2010, the difference in unemployment rates between quartiles 1 and 4 based on the original construction of recession intensity is 2.62 percentage points; in comparison, the difference based on the

alternative construction is 1.86 percentage points (see Figure A1). Since the magnitude of the employment shock is smaller based on the alternative pre-recession period, we would therefore expect the impact on achievement to likewise be attenuated. Using the alternative recession intensity index, we indeed find that the impact on student achievement is attenuated – -0.015 in math and -0.009 in ELA – compared to results based on our principal construction of the recession intensity index (see Table 5, columns 1 and 5). Moreover, the pre-recession unemployment trend based on the alternative recession index is less similar (in levels) across recession intensity quartiles (see Figure A1) than the pre-recession unemployment trend based on our principle construction of recession intensity (see Figure 1); this further supports the use of the principle construction as the primary measure of treatment.

Further, since the recession intensity index was constructed at the county-level, the count of districts (and, by extension, the number of tested students in grades 3-8) are not uniformly distributed across recession intensity quartiles (since the number of districts and grade 3-8 students are not uniformly distributed within county). To construct a second alternative recession intensity index, we weight the recession intensity quartiles by the count of grade 3-8 students in the county, so that the count of tested students is uniformly distributed. We find that our main results are largely insensitive to the re-weighting of counties across recession intensity quartiles by student counts (see Table 5, columns 2 and 6).¹⁹

Second, we examine whether endogenous state- and district-level policy responses bias our main recession effects. To do so, we refine equation (2) by including state-by-year fixed

¹⁹ In results not presented here (but available from the authors upon request), we construct a district-weighted recession intensity index. Namely, we weight recession intensity quartiles by the count of districts in the county, so that county size as measured by district counts is uniformly distributed across recession intensity quartiles. We again find that our main results are largely insensitive to the re-weighting of counties across recession intensity quartiles by district counts.

effects, restricting identification to cross-district, within-state variation, and allowing us to control for endogenous state-level policy responses that may be correlated with the onset of the recession (but to which all districts within a state are subject). We find that the impact on student achievement is qualitatively the same, though slightly attenuated – -0.023 in math and -0.011 in ELA – compared to results based on models that leverage cross-district (and cross-state) variation (see Table 5, columns 3 and 7). We then replace the state-by-year fixed effects with district-by-year fixed effects, allowing us to control for district-specific policy responses that may be correlated with the timing of the onset of the recession. We again find that the impact on student achievement – -0.020 in math and -0.010 in ELA – is qualitatively the same as the main recession effects (see Table 5, columns 4 and 8). Further, results based on models that condition on district-by-year effects are nearly identical to estimates conditional on state-by-year effects, suggesting that district-specific policy responses had little (to no) substantive effect on student achievement beyond any state-specific responses. Therefore, results based on models with state-by-year and district-by-year fixed effects suggest that state-level (and district-level) policy responses – either economic or educational – that may have coincided with the onset of the Great Recession had limited substantive effect on our main results. These results provide additional evidence that the main DD estimates capture the impact of recessionary exposure rather than endogenous state- (and district-) specific responses to the recession.

<Table 5 about here>

Finally, we examine whether recession intensity resulted in endogenous sorting of students. To do so, we re-estimate equation (2) by replacing the dependent variable with proportions of students who are white, black and Hispanic (in three separate regression models).

We focus on the share of students by race/ethnicity since we have variation at the district*grade*year level for these measures of student characteristics.²⁰

If student sorting is limited, we should expect the coefficients on β_q to be small in magnitude and indistinguishable from zero. Table A3 summarizes these results. First, we find no significant or substantive evidence of sorting among Hispanic students across recession intensity quartiles. Second, while we find some evidence of sorting among black and white students, the magnitudes of these estimates, though precisely estimated, are always very small (no more than one-half of one percentage point). And further, our (very modest) estimates suggest positive sorting among black students into districts least affected by the recession and negative sorting (i.e., exit) among white students from districts least affected by the recession. Given that, on average, achievement is lower among minority students than white students, this pattern of student sorting indicates that our main recessionary effects are, at worst, slightly understated. Nonetheless, the very small coefficients indicate that race-based student sorting following the onset of the recession likely had limited (to no) substantive effect on our main results.

Timing of Exposure to the Recession

To what extent does the adverse effect of the recession on student achievement vary by a student's age of first exposure to the recession? Table 6 (and Figure 2) summarizes these results. Recall that cohorts are defined as year of kindergarten entry (i.e., Spring year – grade); thus, earlier cohorts (i.e., cohort 2002) are comprised of students who were older when the Great Recession began than later cohorts (i.e., cohort 2010). For both math and ELA, the recessionary impact is larger (and more negative) for earlier cohorts that experienced the recession in later

²⁰ We note that time-varying measures such as real per pupil instructional expenditures, proportions of students who are ELL, free/reduced lunch, or who have IEPs are not identified in this model, as these variables are not available at the grade level and therefore cannot be linked to cohorts.

grades. Further, the math gradient across cohorts is steeper than the ELA gradient, suggesting that math achievement among older cohorts was more sensitive to the recessionary shock (compared to younger cohorts) than was their ELA achievement.

Among students in the 2002 cohort – those who were in grade 6 in 2007-08, the first year of the recession – those students most impacted by the recession (i.e., quartile 4 of the recession intensity index) realized lower math and ELA achievement, on the order of 0.061 and 0.035 standard deviations, respectively, for each additional school-age year of exposure, compared to students in the 2002 cohort least adversely affected by the recession (i.e., quartile 1). Compare these effects to students in the 2008 cohort – those who were in kindergarten in 2007-08, the first year of the recession. Among students in the 2008 cohort, the math achievement of those most impacted by the recession did not differ compared to students least impacted by the recession. Though the ELA achievement of students in the 2008 cohort who were most impacted by the recession declined by 0.016 standard deviations compared to cohort 2008 students least impacted by the recession, this effect is half the size of the recessionary effect on ELA achievement among students in the 2002 cohort.

In addition to cross-cohort variation in the recessionary impact on student achievement, we again find that the recessionary effect is monotonic within a given cohort. Relative to students in recession intensity quartile 4 – those most adversely impacted by the recession – the recessionary effect (based on the difference-in-differences estimates) is decreasing across quartiles of the recession intensity index.

<Table 6 about here>

<Figure 2 about here>

Heterogeneity of Recessionary Effects

Did exposure to the recession differentially affect student achievement in districts serving higher concentrations of low-income students? Table 7 (and Figure 3) summarizes these results. Among districts serving the highest share of low-income students – those with, on average, 68 percent of students receiving free or reduced-price lunch – students most affected by the recession realized a 0.05 standard deviation decline in math achievement, compared to students least affected by the recession, for every school-age year of exposure to the recession (see Table 7, Panel A). In contrast, among the most economically advantaged districts – those serving, on average, 8 percent of students receiving FRPL – we find no adverse consequences of the recession on student math achievement.

For ELA, there is no recession effect for districts with the highest concentration of students qualifying for FRPL (i.e., $\beta^{q=4} - \beta^{q=1}$). However, among students in quartile 3 districts – those districts with 45 percent of students, on average, qualifying for FRPL – the recession decreased both math and ELA achievement by 0.03 standard deviations, for every school-age year of exposure to the recession. Thus, in districts with above median proportions of students receiving FRPL, the effect of the recession ranged between 0.03 and 0.05 standard deviations. In districts with below median proportions of students receiving FRPL, the effect of the recession is small (between 0.00 and 0.01 standard deviations) and indistinguishable from zero.

<Table 7 about here>

<Figure 3 about here>

Not only did the recessionary effect on achievement vary by a district's concentration of low-income students, we also find that the recessionary effect is concentrated among districts

serving students with greater educational needs, such as special education students and English language learners. Indeed, the recessionary effect on both math and ELA achievement was concentrated among districts serving the highest share of special education students (see Table 7, Panel B) and the highest share of ELL students (see Table 7, Panel C).

Among districts serving, on average, 21 percent of special education students, students most affected by the recession realized a 0.03 standard deviation decline in math achievement and 0.04 standard deviation decline in ELA achievement, compared to students least affected by the recession, for every school-age year of exposure to the recession. In contrast, we do not find any adverse effect of the recession among districts serving the fewest special education students (i.e., districts serving, on average, 4 percent of special education students).

We further find that the recessionary effect on both math and ELA achievement was concentrated among school districts serving higher shares of English language learners (see Table 7, Panel C). Among districts serving the highest share of ELL students – 10 percent, on average – students most affected by the recession realized a 0.04 standard deviation decline in math achievement and 0.03 standard deviation decline in ELA achievement, compared to students least affected by the recession, for every school-age year of exposure to the recession. Among districts serving the lowest share of ELL students (approximately zero percent, on average), there is no adverse impact of the recession on either student math or ELA achievement.

Next, we explore whether the recessionary impact on student achievement was concentrated in districts serving higher concentrations of minority students. Table 8 (and Figure 4) summarizes these results. Among districts serving the highest proportion of black students – 28 percent, on average – students most affected by the recession realized a 0.05 standard deviation decline in math achievement and 0.04 standard deviation decline in ELA achievement,

compared to students least affected by the recession, for every school-age year of exposure to the recession. In contrast, we find no evidence of a recessionary impact on student achievement among districts serving no more than 3 percent of black students, on average (i.e., quartiles 1-3 of percent black),

Though we find limited evidence that the adverse effect of the recession on student achievement was concentrated in districts serving higher shares of Hispanic students (see Table 8, Panel B and Figure 4), we find that the recessionary impact on student achievement was concentrated among districts with the lowest share of white students (see Table 8, Panel C and Figure 4). Specifically, among districts with the lowest share of white students – 35 percent, on average – students most affected by the recession realized a 0.05 standard deviation decline in math achievement and 0.02 standard deviation decline in ELA achievement, compared to students least affected by the recession, for every school-age year of exposure to the recession. Together, findings on the concentration of students by race/ethnicity suggest that the adverse effect of the recession was concentrated among those districts serving the most minority students.

<Table 8 about here>

<Figure 4 about here>

While we find unambiguous evidence that the impact of the recession was most severe in districts serving more low-income and minority students, we do not find any systematic variation in the impact of the recession based on the geographic location of school districts (see Table 9). Results summarized in Table 9 suggest that the economic shock of the Great Recession was not concentrated in urban communities, for example, compared to non-urban (i.e., suburban or rural) communities.

<Table 9 about here>

Potential Mechanisms

There are two potential pathways through which the recession might negatively affect student achievement. First, through the recession's impact on (non-school related) family economic conditions (e.g., employment shocks); and second, through the recession's impact on school resources (e.g., declines in educational spending and reductions in teaching staff). Previously, we observed larger recessionary effects for older students (i.e., earlier cohorts). Given evidence that family resource shocks that occur when children are younger have larger effects on child cognitive development than resource shocks that occur later in life (Duncan, et al., 1998; Duncan, Ziol-Guest, & Kalil, 2010; Votruba-Drzal, 2006), there is reason to believe that the recessionary effects we observe here are operating, in part, through changes in school resources and not entirely through changes in family economic conditions.

To test whether changes in school resources mediate the recessionary effects described above, we construct a measure which captures the change in school resources during the recessionary period. Following the construction of the recession intensity index (see equation (1)), we generate a variable $\Delta Resources_d = \left[\ln \left(\frac{R_{d,2010}}{R_{d,2007}} \right) - \ln \left(\frac{R_{d,2006}}{R_{d,2003}} \right) \right]$, where R_d indicates either counts of teachers or real (\$2010) total instructional expenditures in district d in spring of school year t (e.g., 2010 indicates the 2009-10 school year). We disaggregate $\Delta Resources_d$ into q quartiles (i.e., $\Delta Resources_d^q$); districts in Quartile 1 include those with the least severe resource shock – i.e., the smallest net reduction in resources (either teachers or instructional expenditures) during the recession; districts in Quartile 4 include those with the most severe resource shock – i.e., the largest net reduction in resources during the recession.

Then, we amend equation (2) by interacting $\Delta Resources_d^q$ with the treatment variables $(\sum_{q=1}^Q Recession_d^q * Exposure_{gt})$, as follows:

$$(4) Y_{atg} = \beta_0 + \beta^q (\sum_{q=1}^Q Recession_d^q * Exposure_{gt} * \sum_{q=1}^Q \Delta Resources_d^q) + \mathbf{X}_{at} \boldsymbol{\nu} + \mathbf{X}_{atg} \boldsymbol{\gamma} + \delta_d + \theta_t + \lambda_g + \varepsilon_{atg}$$

Estimates from equation (4) will provide insight into whether recessionary effects on student achievement vary by the magnitude of the school resource shock.²¹ From equation (4), we recover the difference-in-difference-in-differences (DDD) estimand of interest, as follows:

$\delta^{DDD} = ((\beta^{(q=4)} - \beta^{(q=1)})) \times (\Delta Resources^{(q=4)} - \Delta Resources^{(q=\in 1,2,3)})$, where $(\beta^{(q=4)} - \beta^{(q=1)})$ is the difference-in-differences estimate (from equation (2)) of the impact of the recession on student achievement. The DDD estimand (δ^{DDD}) indicates how recessionary effects on achievement (i.e., $\beta^{(q=4)} - \beta^{(q=1)}$) vary across school resource shocks (i.e., $\Delta Resources_d^{q=4} - \Delta Resources_d^{q=\in 1,2,3}$). If δ^{DDD} is statistically (and substantively) indistinguishable from zero, then we can conclude that the effect of the recession did not vary with changes in school resources and that the effect is primarily due to changes in family economic resources.

Table 10 summarizes the DDD estimates (Table A4 summarizes the parameter estimates from equation (4)). We find that districts with the largest reductions in the stock of teachers (i.e., $\Delta Resources_d^{q=4}$, which corresponds to approximately a net reduction of 29 percent) had significantly worse achievement outcomes due to recessionary shocks, on the order of -0.04 to -0.048 standard deviations in math and -0.04 to -0.055 standard deviations in ELA. Further, while

²¹ Note that β^q in equation (4) is a q -by- q matrix that produces 16 coefficients. Table A4 summarizes these coefficient estimates (by subject).

districts with the largest decline in instructional expenditures experienced worse achievement outcomes, the estimates are only significant in two cases for ELA. Together, this evidence suggests that the recessionary effect on student achievement is due, in part, to large changes in school-specific resources, driven primarily by changes in teacher labor supply. This pattern of results is consistent with evidence presented earlier that the recessionary effect was concentrated among older students (relative to their younger counterparts).

<Table 10 about here>

Conclusion

The Great Recession, which began in December 2007, was the most severe economic downturn in the United States since the Great Depression. In this paper, we show that the onset of the Great Recession had severe and adverse consequences for the academic achievement of students. Moreover, we show that the adverse effects of the recession were not distributed equally among the population of U.S. students.

First, the academic achievement of older students – those in middle grades (i.e., grades 5-7) – was more adversely affected by the recession than the achievement of their younger counterparts. As an explanation for this result, we find that recessionary effects are concentrated in districts where teacher reductions were most pronounced, suggesting that recessionary effects on student achievement were mediated by recessionary effects on school resources. Though we know that nearly 300,000 school employees were laid off because of the recession (Evans, Schwab and Wager, 2017), no evidence exists to indicate whether these layoffs were distributed differently across grades and/or subjects. If, for example, schools systematically maintained staff positions for younger students and targeted layoffs in later grades, then the disproportionate reduction in teacher human capital may have led to differential effects for older students, due to

the critical role that teacher quality plays in driving student achievement (Aaronson, Barrow, & Sander, 2007; Chetty, Friedman, & Rockoff, 2014; Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004). The differential effect by student age may also reflect differences in academic skill acquisition, such that the academic skills required of students in later grades may be more vulnerable to economic shocks that reduce the human and financial capital available to schools. This result may also reveal differences in the academic resiliency of students, such that younger students may be more insulated from school resource shocks during recessionary events than their older counterparts. Further understanding the possible mechanisms through which economic shocks differentially impact students by age of exposure is an important area for further research.

Second, the Great Recession exacerbated the inequality of student achievement outcomes across school districts serving different student populations (e.g., by socioeconomic status, ELL and special education status, and race/ethnicity). Indeed, we find that the adverse effects of the recession were concentrated among school districts serving higher concentrations of low-income and minority students. It is known that districts serving more low-income and minority students tend to rely more on state aid compared to more economically advantaged districts that rely more on local property wealth to raise educational revenues. Evans, Schwab and Wagner (2017) show that districts most reliant on state aid, and therefore more likely to be economically disadvantaged, were more adversely affected by the recession due to declines in the two principle sources of tax revenue – income and sales taxes – that support state education spending. Thus, it is no surprise that the adverse effect of the recession on achievement was also disproportionately felt by more economically disadvantaged school districts.

In response to the Great Recession, President Obama signed into law the American Recovery and Reinvestment Act (ARRA), which appropriated \$97.4 billion in fiscal stimulus to bolster education, the single largest component of which included educational aid via the State Fiscal Stabilization Fund (SFSF).²² Though the stimulus aid was designed to stabilize state and district education budgets to avoid reductions in essential educational services, our results indicate that the distribution of ARRA aid to states (and districts) did not align with how the impact of the recession on student achievement was distributed across school districts. Notably, under ARRA, the majority of federal aid was distributed to states based on population shares and allocated to districts (within states) based on pre-recession funding formula (Evans, Schwab and Wagner, 2017; Steinberg, Quinn & Anglum, 2017). However, the provision of federal fiscal stimulus was not based on where the recession was most severe (i.e., where employment losses were greatest) or where the effects of the recession on student achievement were most pronounced (e.g., in districts serving the largest shares of low-income and black students). Our results therefore point to the need for policymakers and school leaders to consider variation in the recession's effect on local economic conditions as well as specific features of school districts when determining the distribution of stimulus aid during future recessionary events.

Our results reveal that the achievement trajectories for particular segments of the school-age population were substantially attenuated by the Great Recession. The impact of the recession for disadvantaged subgroups – upwards of 0.05 standard deviations for each school-age year of exposure to the recession – was larger than the effects of known educational interventions. For example, increases in per pupil spending of \$424 following education finance reform have been

²² SFSF consisted of \$53.6 billion, of which \$48.6 billion was apportioned to state governments based on the relative population of individuals within the state and then allocated to school districts (within states) based on a state's pre-existing funding formula.

shown to increase student achievement by 0.01 standard deviations (Lafortune, Rothstein and Schanzenbach, 2017); and class size reductions of one pupil result in 0.023 standard deviations of achievement (Chetty, et al., 2011; Fredriksson, Öckert and Oosterbeek, 2012; Krueger, 1999).

Finally, since there are long-term effects of student achievement on adult earnings (Chetty, et al., 2011; Chetty, et al., 2014; Fredriksson, Öckert and Oosterbeek, 2012), the consequences of the Great Recession will continue to be felt by students most impacted by the recession. The recessionary impact on student achievement identified here, coupled with the known effects of student achievement on future earnings, suggest that students who experienced the Great Recession during their school-age years will likely suffer long-term economic declines, compared to students least impacted by the Great Recession. Therefore, future efforts to mitigate the longer-term effects of economic downturns must address the short-term and disparate impact that economic recessions have on student achievement.

References

- Aaronson, D., Barrow, L., & Sander, W. (2007). Teachers and student achievement in the Chicago public high schools. *Journal of Labor Economics*, 25(1), 95-135.
- Ananat, E. O., Gassman-Pines, A., Francis, D. V., & Gibson-Davis, C. M. (2011). Children left behind: The effects of statewide job loss on student achievement (No. w17104). *National Bureau of Economic Research*.
- Angrist, J.D., & Pischke, J. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton: Princeton University Press.
- Autor, D. H., Dorn, D., & Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8, 205-240.
- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1), 249-275.
- Business Cycle Dating Committee, National Bureau of Economic Research (September 20, 2010). <http://www.nber.org/cycles/sept2010.html>
- Chakrabarti, R., & Livingston, M. (2013). The long road to recovery: New York Schools in the aftermath of the Great Recession. *FRB of New York Staff Report*, (631).
- Chakrabarti, R., Livingston, M., & Roy, J. (2014). Did cuts in state aid during the Great Recession lead to changes in local property taxes?. *Education Finance and Policy*, 9(4), 383-416.
- Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *The Quarterly Journal of Economics*, 126(4), 1593-1660.
- Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *The American Economic Review*, 104(9), 2633-2679.
- Dahl, G. B., & Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *The American Economic Review*, 102(5), 1927-1956.
- Duncan, G. J., Yeung, W. J., Brooks-Gunn, J., & Smith, J. R. (1998). How much does childhood poverty affect the life chances of children?. *American sociological review*, 406-423.
- Duncan, G. J., Ziol-Guest, K. M., & Kalil, A. (2010). Early-childhood poverty and adult attainment, behavior, and health. *Child development*, 81(1), 306-325.
- Evans, W. N., Schwab, R. M., & Wagner, K. L. (2017). The Great Recession and Public Education. *Unpublished manuscript*.
- Fogli, A., Hill, E., & Perri, F. (2015). The Geography of the Great Recession/Spatial Business Cycles. *Unpublished manuscript*.

- Fredriksson, P., Öckert, B., & Oosterbeek, H. (2012). Long-term effects of class size. *The Quarterly Journal of Economics*, 128(1), 249-285.
- Frey, W. (2009). The great American migration slowdown. *Brookings Institution, Washington, DC*.
- Grusky, D. B., Western, B., & Wimer, C. (Eds.). (2011). *The great recession*. Russell Sage Foundation.
- Hurd, M. D., & Rohwedder, S. (2010). Effects of the financial crisis and great recession on American households (No. w16407). *National Bureau of Economic Research*.
- Jackson, C. K., Johnson, R. C., & Persico, C. (2016). The effects of school spending on educational and economic outcomes: Evidence from school finance reforms. *The Quarterly Journal of Economics*, 131(1), 157-218.
- Katz, L. (2010, April). Long-term unemployment in the Great Recession. In *Testimony for the Joint Economic Committee, US Congress, April* (Vol. 29).
- Kochhar, R., & Fry, R. (2014). Wealth inequality has widened along racial, ethnic lines since end of Great Recession. *Pew Research Center*, 12, 1-15.
- Krueger, A. B. (1999). Experimental estimates of education production functions. *The Quarterly Journal of Economics*, 114(2), 497-532.
- Lafortune, Julien, Rothstein, Jesse and Schanzenbach, Diane W. (in press). "School Finance Reform and the Distribution of Student Achievement." *American Economic Journal: Applied Economics*.
- Leachman, M., & Mai, C. (2014). Most states still funding schools less than before the recession. *Center on Budget and Policy Priorities*.
- Reardon, S.F., Kaolgrides, D. and Ho, A. (June 2017). Linking U.S. School District Test Score Distributions to a Common Scale. <https://cepa.stanford.edu/sites/default/files/wp16-09-v201706.pdf>
- Reardon, S. F., Shear, B. R., Castellano, K. E., & Ho, A. D. (2017). Using Heteroskedastic Ordered Probit Models to Recover Moments of Continuous Test Score Distributions From Coarsened Data. *Journal of Educational and Behavioral Statistics*, 42(1), 3-45.
- Reardon, S.F. & Fahle, E. (2016). Between-District Test Score Variation, 2009-2012. *Unpublished manuscript*.
- Reardon, S., D. Kalogrides, and K. Shores. The geography of racial/ethnic test score gaps. (2016). *Unpublished Manuscript*. <https://cepa.stanford.edu/sites/default/files/wp16-10-v201701.pdf>
- Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, schools, and academic achievement. *Econometrica*, 73(2), 417-458.
- Rockoff, J. E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. *The American Economic Review*, 94(2), 247-252.
- Steinberg, M, R. Quinn & C. Anglum. (2017). Education finance reform and the Great Recession: Did state policy and fiscal federalism improve education spending, school resources and student achievement in Pennsylvania? *Unpublished manuscript*.

- Stevens, A. H., & Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Economics of Education Review*, 30(2), 289-299.
- Votruba-Drzal, E. (2006). Economic disparities in middle childhood development: Does income matter?. *Developmental psychology*, 42(6), 1154.
- Wolff, E., Owens, L. A., & Burak, E. (2011). How much wealth was destroyed in the great recession. In D. B. Grusky, B. Western, & C. Wimer (Eds.), *The great recession* (pp. 127-158). New York: Russell Sage Foundation.
- Yagan, D. (2016). Is the Great Recession Really Over? Longitudinal Evidence of Enduring Employment Impacts. *Unpublished Manuscript*.

Tables & Figures

Table 1. County-Level Economic Characteristics, by Recession Intensity Quartile

Economic Characteristic	Recession Intensity Quartile										% Change
	Analytic Sample		Q1		Q2		Q3		Q4		
	Pre	During	Pre	During	Pre	During	Pre	During	Pre	During	
Unemployment Rate	.057 (.018)	.062 (.028)	.058 (.020)	.057 (.025)	.056 (.018)	.059 (.026)	.057 (.018)	.064 (.028)	.057 (.018)	.067 (.033)	17.9%
Unemployment Insurance	105.6 (57.04)	164.3 (146.5)	95.6 (52.3)	134.0 (116.0)	110.5 (58.8)	166.1 (142.4)	112.0 (57.2)	179.6 (153.8)	104.3 (58.2)	177.8 (164.9)	19.6%
Child Poverty Rate	.177 (.078)	.197 (.084)	.193 (.082)	.211 (.087)	.174 (.078)	.192 (.083)	.169 (.075)	.190 (.081)	.172 (.076)	.196 (.082)	4.2%
Household Earnings	14,173 (4494.5)	17,872 (5708.7)	13,175 (4184.9)	17,133 (5658.5)	14,567 (4584.3)	18,491 (5896.9)	14,743 (4643.4)	18,433 (5798.3)	14,211 (4388.0)	17,433 (5342.1)	-5.8%
Income (per capita)	22,181 (5629.6)	29,125 (7620.2)	21,081 (5057.3)	28,260 (7179.1)	22,788 (5746.3)	29,991 (7730.4)	22,762 (5894.7)	29,709 (8055.8)	22,099 (5616.5)	28,541 (7344.8)	-3.7%
County*Year Observations	12,007	12,009	3,010	3,011	2,990	2,990	3,011	3,012	2,996	2,996	

Notes. Mean (standard deviation) reported. *Pre* indicates the pre-recession period (fiscal years 2002-2005) and *During* indicates the period during the recession (fiscal years 2006-2009). For *Unemployment* and *Child Poverty*, the mean (standard deviation) rates are reported in proportions. For *Unemployment Insurance*, *Household Earnings* and *Income (per capita)*, the mean (standard deviation) are reported in real \$2013. *Q4-Q1* reports the percent change in economic characteristics (between the pre- and during-recession periods) for counties in quartile four of recession intensity relative to the percent change in economic characteristics for counties in quartile one of recession intensity (i.e., $\ln\left(\frac{Q4_{During}}{Q4_{Pre}}\right) - \ln\left(\frac{Q1_{During}}{Q1_{Pre}}\right)$).

Table 2. District Characteristics, by Recession Intensity Quartile

District Characteristic	Analytic Sample	Recession Intensity Quartile			
		Q1	Q2	Q3	Q4
Enrollment (grades 3-8)	1997.1 (7237.07)	1784.2 (10935.56)	1762.9 (4863.54)	2083.3 (6938.01)	2446.5 (6875.55)
Class Size	16.8 (264.37)	15.2 (75.04)	15.1 (35.07)	19.7 (476.56)	16.8 (14.97)
Free/Reduced- Price Lunch	0.44 (0.22)	0.49 (0.21)	0.40 (0.23)	0.42 (0.22)	0.47 (0.21)
White	0.73 (0.27)	0.71 (0.28)	0.73 (0.28)	0.74 (0.27)	0.73 (0.26)
Hispanic	0.12 (0.20)	0.13 (0.21)	0.12 (0.19)	0.11 (0.19)	0.14 (0.20)
Black	0.08 (0.17)	0.09 (0.19)	0.09 (0.17)	0.08 (0.17)	0.07 (0.15)
Asian	0.02 (0.05)	0.02 (0.05)	0.03 (0.06)	0.02 (0.05)	0.01 (0.03)
Urban	0.06	0.05	0.07	0.07	0.06
Suburban	0.24	0.13	0.30	0.29	0.14
Rural	0.49	0.59	0.44	0.46	0.54
Town	0.21	0.23	0.19	0.18	0.26
Total Revenue	12799.8 (5909.57)	12294.7 (5725.13)	14097.6 (6055.09)	12640.7 (5667.88)	11311.3 (5735.45)
Instructional Expenditures	6484.2 (2519.04)	6172.5 (1997.03)	7227.9 (3002.47)	6401.7 (2331.63)	5637.4 (1898.61)
Districts	11,748	2,103	3,879	3,519	2,266
District*Year Observations	56,191	9,972	18,513	16,830	10,876
Total Students	106,000,000	16,300,000	30,700,000	33,200,000	25,300,000

Notes. Data are for the 2008-09 through 2012-13 school years. Mean (standard deviation) reported, except for the geographic locale of districts (Urban, Suburban, Rural and Town) which are reported in proportions. *Enrollment* is district-level enrollment of students in grades 3-8; *Class Size* is the ratio of K-12 enrollment to teachers. *Total Revenue* and *Instructional Expenditures* are in per pupil amounts and reported in \$2013. District totals are for the ELA achievement sample.

Table 3. Achievement Outcomes, by Recession Intensity Quartile

	Recession Intensity Quartile					P-value from F- Test: $Q4=Q1$
	Analytic Sample	Q1	Q2	Q3	Q4	
Panel A: Math Achievement						
District Mean	0.014 (0.345)	-0.012 (0.335)	0.023 (0.379)	0.015 (0.349)	0.014 (0.297)	0.011
Districts	11,730	2,104	3,872	3,512	2,261	
District*Year*Grade Observations	308,650	53,808	102,147	92,548	60,147	
Panel A: ELA Achievement						
District Mean	0.012 (0.340)	-0.056 (0.338)	0.036 (0.369)	0.005 (0.344)	0.030 (0.291)	0.000
Districts	11,748	2,103	3,879	3,519	2,266	
District*Year*Grade Observations	315,034	54,670	103,693	94,966	61,705	

Notes. Data are for the 2008-09 through 2012-13 school years. *District Mean* is district achievement averaged across multiple grades and years (where grade-level achievement is standardized to have mean zero and standard deviation one). Means and standard deviations are weighted by $1/\hat{\sigma}_{dgt}^2$ (where d denotes district, g denotes grade (3-8) and t denotes school year). $Q4=Q1$ presents the p-value of a test of equality of means, by subject, between the first and fourth quartiles of the recession intensity index.

Table 4. Recession Effects on Student Achievement

	Math		ELA	
	(1)	(2)	(3)	(4)
$RI^{q=1} * Exposure = \beta^{(q=1)}$	0.008 (.006)		0.040*** (.004)	
$RI^{q=2} * Exposure = \beta^{(q=2)}$	-0.010*** (.004)		0.031*** (.003)	
$RI^{q=3} * Exposure = \beta^{(q=3)}$	-0.017*** (.004)		0.028*** (.003)	
$RI^{q=4} * Exposure = \beta^{(q=4)}$	-0.025*** (.004)		0.020*** (.003)	
$RI^{Linear} * Exposure$		-0.010*** (.002)		-0.007*** (.002)
DD Estimates:				
$\beta^{(q=4)} - \beta^{(q=1)}$	-0.033*** (.007)		-0.021*** (.005)	
$\beta^{(q=4)} - \beta^{(q=2)}$	-0.015*** (.006)		-0.011** (.004)	
$\beta^{(q=4)} - \beta^{(q=3)}$	-0.007 (.006)		-0.009** (.004)	
Districts	11,730		11,748	
District*Year*Grade Observations	308,650		315,034	

Notes. Each column represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. RI^q is an indicator for the q th recession intensity quartile and RI^{Linear} is the linear recession intensity index (standardized to have mean zero and standard deviation one); *Exposure* is the number of school-age years of exposure to the recession (that varies at the cohort-level). All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 5. Recession Effects on Student Achievement: Sensitivity Analysis

	Math				ELA			
	Recession Intensity Index		State Response	District Response	Recession Intensity Index		State Response	District Response
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$RI^{q=1} * Exposure = \beta^{(q=1)}$	-0.002 (.005)	-0.001 (.004)	0.004 (.005)	0.002 (.005)	0.034*** (.004)	0.035*** (.003)	0.033*** (.004)	0.032*** (.004)
$RI^{q=2} * Exposure = \beta^{(q=2)}$	-0.014*** (.004)	-0.007* (.004)	-0.011*** (.003)	-0.01*** (.003)	0.029*** (.003)	0.032*** (.003)	0.027*** (.002)	0.026*** (.003)
$RI^{q=3} * Exposure = \beta^{(q=3)}$	-0.016*** (.004)	-0.019*** (.004)	-0.015*** (.003)	-0.015*** (.003)	0.028*** (.003)	0.028*** (.003)	0.029*** (.002)	0.029*** (.003)
$RI^{q=4} * Exposure = \beta^{(q=4)}$	-0.017*** (.004)	-0.026*** (.004)	-0.019*** (.004)	-0.018*** (.004)	0.025*** (.003)	0.020*** (.003)	0.021*** (.003)	0.022*** (.004)
DD Estimates:								
$\beta^{(q=4)} - \beta^{(q=1)}$	-0.015** (.006)	-0.025*** (.006)	-0.023*** (.007)	-0.020*** (.007)	-0.009* (.005)	-0.015*** (.005)	-0.011** (.005)	-0.010* (.006)
$\beta^{(q=4)} - \beta^{(q=2)}$	-0.003 (.005)	-0.019*** (.006)	-0.008 (.005)	-0.008 (.005)	-0.005 (.004)	-0.012*** (.004)	-0.006 (.005)	-0.004 (.005)
$\beta^{(q=4)} - \beta^{(q=3)}$	-0.001 (.006)	-0.007 (.006)	-0.004 (.005)	-0.002 (.006)	-0.003 (.005)	-0.008* (.004)	-0.007 (.005)	-0.006 (.005)
Districts	11,730	11,730	11,730	11,549	11,748	11,748	11,748	11,581
District*Year*Grade Observations	308,650	308,650	308,650	307,322	315,034	315,034	315,034	313,732

Notes. Each column represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. In columns (1) and (5), we construct recession intensity quartiles based on the pre-recession period – fiscal years 2000-2003 – as in Yagan (2016). In columns (2) and (6), we construct weighted quartiles of the recession intensity index that are based on district-level enrollment in grades 3-8. In columns (3) and (7), we add state-by-year fixed effects to equation (2). In columns (4) and (8), we add district-by-year fixed effects to equation (2). All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 6. Recession Effects on Student Achievement, by Cohort (Age of Exposure)

	Cohort 2002	Cohort 2003	Cohort 2004	Cohort 2005	Cohort 2006	Cohort 2007	Cohort 2008	P-value from F-Test: 2002=2003=.. 2007=2008
Panel A: Math								
$RI^{q=1} * Cohort_c = \beta_c^{(q=1)}$	0.033*** (.008)	0.027*** (.008)	0.010 (.007)	-0.002 (.007)	-0.011* (.006)	-0.013*** (.005)	-0.010** (.005)	0.000
$RI^{q=2} * Cohort_c = \beta_c^{(q=2)}$	-0.004 (.006)	-0.008 (.005)	-0.014*** (.005)	-0.018*** (.004)	-0.020*** (.004)	-0.021*** (.003)	-0.010*** (.003)	0.000
$RI^{q=3} * Cohort_c = \beta_c^{(q=3)}$	-0.021*** (.005)	-0.021*** (.005)	-0.022*** (.005)	-0.023*** (.005)	-0.020*** (.004)	-0.012*** (.004)	-0.009*** (.003)	0.028
$RI^{q=4} * Cohort_c = \beta_c^{(q=4)}$	-0.028*** (.006)	-0.033*** (.005)	-0.032*** (.006)	-0.030*** (.005)	-0.026*** (.005)	-0.018*** (.004)	-0.011*** (.004)	0.004
DD Estimates:								
$\beta_c^{(q=4)} - \beta_c^{(q=1)}$	-0.061*** (.011)	-0.059*** (.011)	-0.042*** (.010)	-0.027*** (.009)	-0.015* (.008)	-0.005 (.007)	-0.001 (.006)	
$\beta_c^{(q=4)} - \beta_c^{(q=2)}$	-0.025*** (.009)	-0.025*** (.009)	-0.017** (.008)	-0.012* (.007)	-0.006 (.006)	0.003 (.005)	-0.001 (.005)	
$\beta_c^{(q=4)} - \beta_c^{(q=3)}$	-0.008 (.009)	-0.012 (.009)	-0.009 (.008)	-0.007 (.007)	-0.007 (.006)	-0.006 (.005)	-0.002 (.005)	
Districts								11,730
District*Year*Grade Observations								308,650
Panel B: ELA								
$RI^{q=1} * Cohort_c = \beta_c^{(q=1)}$	0.031*** (.007)	0.036*** (.007)	0.047*** (.006)	0.051*** (.005)	0.051*** (.005)	0.045*** (.004)	0.036*** (.004)	0.000

$RI^{q=2} * Cohort_c = \beta_c^{(q=2)}$	0.024*** (.004)	0.030*** (.004)	0.039*** (.004)	0.039*** (.003)	0.035*** (.003)	0.031*** (.003)	0.025*** (.003)	0.000
$RI^{q=3} * Cohort_c = \beta_c^{(q=3)}$	0.008** (.004)	0.022*** (.004)	0.034*** (.004)	0.041*** (.003)	0.039*** (.003)	0.037*** (.002)	0.025*** (.002)	0.000
$RI^{q=4} * Cohort_c = \beta_c^{(q=4)}$	-0.004 (.005)	0.009* (.006)	0.023*** (.005)	0.033*** (.005)	0.033*** (.004)	0.029*** (.003)	0.020*** (.003)	0.000
DD Estimates:								
$\beta_c^{(q=4)} - \beta_c^{(q=1)}$	-0.035*** (.009)	-0.027*** (.009)	-0.025*** (.008)	-0.018*** (.007)	-0.019*** (.006)	-0.016*** (.005)	-0.016*** (.005)	
$\beta_c^{(q=4)} - \beta_c^{(q=2)}$	-0.028*** (.007)	-0.021*** (.008)	-0.016** (.007)	-0.006 (.006)	-0.003 (.005)	-0.002 (.004)	-0.005 (.004)	
$\beta_c^{(q=4)} - \beta_c^{(q=3)}$	-0.012* (.007)	-0.012 (.008)	-0.011 (.007)	-0.008 (.006)	-0.007 (.005)	-0.007* (.004)	-0.004 (.004)	
Districts	11,748							
District*Year*Grade Observations	315,034							

Notes. Each panel represents a separate regression based on equation (3). Coefficients with robust standard errors (clustered at the district level) are reported. Table A1 summarizes how cohorts are defined. All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 7. Recession Effects on Student Achievement, by Student Characteristics

	Math				ELA			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Panel A: %FRPL								
RI ^{q=1} *Exposure = $\beta(q=1)$	0.017 (.013)	-0.022*** (.009)	-0.006 (.011)	0.022*** (.009)	0.046*** (.007)	0.027*** (.007)	0.030*** (.005)	0.047*** (.007)
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.000 (.005)	-0.014** (.006)	-0.012 (.010)	-0.013* (.008)	0.030*** (.004)	0.028*** (.005)	0.031*** (.007)	0.033*** (.005)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.006 (.005)	-0.013 (.008)	-0.028*** (.008)	-0.021*** (.008)	0.031*** (.004)	0.024*** (.005)	0.031*** (.007)	0.033*** (.005)
RI ^{q=4} *Exposure = $\beta(q=4)$	0.005 (.009)	-0.021*** (.008)	-0.039*** (.006)	-0.031*** (.007)	0.046*** (.006)	0.016*** (.006)	-0.002 (.006)	0.033*** (.007)
Quartile Mean	0.082	0.291	0.446	0.676	0.082	0.291	0.446	0.676
DD Estimate:								
$\beta(q=4) - \beta(q=1)$	-0.011 (.016)	0.001 (.012)	-0.033*** (.013)	-0.053*** (.011)	0.000 (.009)	-0.011 (.009)	-0.032*** (.008)	-0.014 (.010)
$\beta(q=4) - \beta(q=2)$	0.005 (.010)	-0.007 (.010)	-0.027** (.012)	-0.018* (.011)	0.016*** (.007)	-0.012* (.007)	-0.032*** (.009)	0.000 (.009)
$\beta(q=4) - \beta(q=3)$	0.011 (.010)	-0.008 (.012)	-0.011 (.010)	-0.010 (.011)	0.015*** (.007)	-0.008 (.008)	-0.026*** (.008)	0.000 (.009)
Panel B: %IEP								
RI ^{q=1} *Exposure = $\beta(q=1)$	0.013 (.010)	0.020* (.010)	-0.013 (.011)	0.003 (.009)	0.034*** (.009)	0.050*** (.008)	0.034*** (.006)	0.040*** (.006)
RI ^{q=2} *Exposure = $\beta(q=2)$	0.010* (.005)	0.002 (.007)	-0.036*** (.008)	-0.022*** (.007)	0.032*** (.004)	0.047*** (.005)	0.014*** (.005)	0.023*** (.005)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.002 (.008)	-0.018*** (.007)	-0.021*** (.006)	-0.027*** (.006)	0.034*** (.006)	0.035*** (.004)	0.025*** (.005)	0.013*** (.005)

RI ^{q=4} *Exposure = $\beta^{(q=4)}$	-0.001 (.010)	-0.025*** (.006)	-0.035*** (.007)	-0.027*** (.010)	0.052*** (.006)	0.025*** (.005)	0.001 (.007)	0.000 (.006)
Quartile Mean	0.037	0.120	0.151	0.211	0.037	0.120	0.151	0.214
DD Estimate:								
$\beta^{(q=4)} - \beta^{(q=1)}$	-0.014 (.015)	-0.045*** (.012)	-0.022* (.013)	-0.030** (.014)	0.018* (.010)	-0.026** (.009)	-0.033*** (.009)	-0.039*** (.009)
$\beta^{(q=4)} - \beta^{(q=2)}$	-0.011 (.012)	-0.027*** (.009)	0.000 (.010)	-0.005 (.012)	0.020*** (.007)	-0.023*** (.007)	-0.013 (.009)	-0.023*** (.008)
$\beta^{(q=4)} - \beta^{(q=3)}$	0.001 (.013)	-0.007 (.010)	-0.014 (.009)	-0.000 (.012)	0.018** (.009)	-0.010 (.007)	-0.025*** (.009)	-0.012 (.008)

Panel C: %ELL

RI ^{q=1} *Exposure = $\beta^{(q=1)}$	0.002 (.011)	-0.005 (.011)	0.002 (.011)	0.013 (.008)	0.035*** (.008)	0.032*** (.008)	0.044*** (.006)	0.041*** (.006)
RI ^{q=2} *Exposure = $\beta^{(q=2)}$	0.024*** (.008)	-0.029*** (.008)	-0.011 (.007)	-0.015*** (.005)	0.049*** (.006)	0.019** (.006)	0.026*** (.005)	0.030*** (.004)
RI ^{q=3} *Exposure = $\beta^{(q=3)}$	0.032*** (.006)	-0.032*** (.008)	-0.039*** (.006)	-0.023*** (.006)	0.051*** (.005)	0.020** (.007)	0.019*** (.004)	0.023*** (.004)
RI ^{q=4} *Exposure = $\beta^{(q=4)}$	0.025*** (.005)	-0.030*** (.009)	-0.047*** (.009)	-0.029*** (.005)	0.050*** (.005)	0.024*** (.009)	0.003 (.007)	0.014*** (.005)
Quartile Mean	0.000	0.002	0.010	0.100	0.000	0.002	0.010	0.100
DD Estimate:								
$\beta^{(q=4)} - \beta^{(q=1)}$	0.023* (.012)	-0.025* (.014)	-0.049*** (.014)	-0.042*** (.010)	0.015* (.009)	-0.008 (.011)	-0.041*** (.009)	-0.027*** (.008)
$\beta^{(q=4)} - \beta^{(q=2)}$	0.002 (.009)	-0.000 (.012)	-0.036*** (.011)	-0.015* (.008)	0.002 (.008)	0.005 (.010)	-0.024*** (.009)	-0.016*** (.006)
$\beta^{(q=4)} - \beta^{(q=3)}$	-0.007 (.008)	0.002 (.012)	-0.007 (.011)	-0.007 (.008)	-0.000 (.006)	0.004 (.011)	-0.016* (.008)	-0.009 (.007)

Districts

11,670

11,697

District*Year*Grade
Observations

307,696

314,083

Notes. Each panel and subject represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. For each district characteristic – the proportion of students eligible for free/reduced-price lunch (FRPL), the proportion of students receiving special education services who receive an IEP, or individualized education plan, and the proportion of students who are English language learners (ELL) – quartiles were created based on values from the 2007-08 school year. Districts with the lowest proportion of students, by characteristic, are included in Quartile 1; districts with the highest proportion of students, by characteristics, are included in Quartile 4. Proportions based on the 2007-08 school year of the population classified as FRPL, IEP and ELL, respectively, for each demographic quartile are reported and labeled as quartile mean. All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 8. Recession Effects on Student Achievement, by District Racial/Ethnic Composition

	Math				ELA			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Panel A: %Black								
RI ^{q=1} *Exposure = $\beta(q=1)$	-0.015 (.012)	-0.002 (.010)	-0.011 (.009)	0.017** (.008)	0.033*** (.008)	0.043*** (.008)	0.034*** (.007)	0.042*** (.006)
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.016* (.009)	-0.008 (.006)	0.001 (.007)	-0.015*** (.005)	0.045*** (.007)	0.031*** (.006)	0.042*** (.005)	0.024*** (.004)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.014* (.008)	-0.017*** (.006)	-0.010* (.005)	-0.021*** (.006)	0.032*** (.008)	0.038*** (.005)	0.033*** (.004)	0.024*** (.004)
RI ^{q=4} *Exposure = $\beta(q=4)$	-0.035*** (.009)	-0.005 (.008)	-0.013* (.008)	-0.032*** (.005)	0.038*** (.009)	0.052*** (.006)	0.036*** (.006)	0.005 (.004)
Quartile Mean	0.002	0.011	0.030	0.281	0.002	0.011	0.030	0.281
DD Estimate:								
$\beta(q=4) - \beta(q=1)$	-0.021 (.015)	-0.003 (.013)	-0.002 (.012)	-0.049*** (.010)	0.005 (.011)	0.009 (.009)	0.002 (.009)	-0.037*** (.007)
$\beta(q=4) - \beta(q=2)$	-0.019 (.012)	0.003 (.010)	-0.015 (.010)	-0.017** (.008)	-0.007 (.011)	0.021*** (.008)	0.002 (.009)	-0.019*** (.006)
$\beta(q=4) - \beta(q=3)$	-0.021* (.012)	0.012 (.010)	-0.003 (.009)	-0.010 (.008)	0.006 (.012)	0.014* (.007)	0.003 (.007)	-0.018*** (.006)
Panel B: %Hispanic								
RI ^{q=1} *Exposure = $\beta(q=1)$	-0.014 (.017)	0.004 (.011)	0.011 (.009)	0.013 (.009)	0.030*** (.006)	0.040*** (.009)	0.048*** (.006)	0.040*** (.006)
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.027*** (.006)	-0.014*** (.006)	-0.018** (.008)	0.003 (.005)	0.028*** (.006)	0.027*** (.005)	0.025*** (.006)	0.037*** (.004)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.030*** (.006)	-0.015*** (.006)	-0.029*** (.007)	-0.005 (.007)	0.037*** (.007)	0.028*** (.004)	0.018*** (.005)	0.035*** (.004)

RI ^{q=4} *Exposure = $\beta^{(q=4)}$	-0.041*** (.008)	-0.026*** (.008)	-0.026*** (.008)	-0.022*** (.006)	0.027*** (.008)	0.021*** (.006)	0.010 (.006)	0.024*** (.005)
Quartile Mean	0.004	0.019	0.058	0.368	0.004	0.019	0.058	0.369
DD Estimate:								
$\beta^{(q=4)} - \beta^{(q=1)}$	-0.026 (.019)	-0.030** (.014)	-0.037*** (.012)	-0.035*** (.010)	-0.003 (.008)	-0.019* (.011)	-0.038*** (.009)	-0.016* (.009)
$\beta^{(q=4)} - \beta^{(q=2)}$	-0.013 (0.010)	-0.012 (0.010)	-0.008 (0.012)	-0.025*** (0.008)	-0.002 (0.009)	-0.006 (0.007)	-0.015* (0.009)	-0.013* (0.007)
$\beta^{(q=4)} - \beta^{(q=3)}$	-0.011 (0.010)	-0.011 (0.010)	0.004 (0.011)	-0.017* (0.009)	-0.010 (0.010)	-0.008 (0.007)	-0.008 (0.008)	-0.011 (0.007)

Panel C: %White

RI ^{q=1} *Exposure = $\beta^{(q=1)}$	0.015* (.008)	0.005 (.012)	-0.008 (.009)	-0.027*** (.010)	0.042*** (.006)	0.041*** (.008)	0.038*** (.009)	0.023*** (.007)
RI ^{q=2} *Exposure = $\beta^{(q=2)}$	-0.011* (.006)	-0.002 (.007)	-0.013*** (.005)	-0.026*** (.006)	0.030*** (.004)	0.032*** (.005)	0.034*** (.004)	0.021*** (.005)
RI ^{q=3} *Exposure = $\beta^{(q=3)}$	-0.020*** (.006)	-0.010* (.006)	-0.023*** (.007)	-0.025*** (.006)	0.029*** (.004)	0.028*** (.004)	0.028*** (.005)	0.026*** (.005)
RI ^{q=4} *Exposure = $\beta^{(q=4)}$	-0.031*** (.006)	-0.015** (.007)	-0.022** (.010)	-0.045*** (.009)	0.021*** (.006)	0.015*** (.005)	0.029*** (.007)	0.018*** (.006)
Quartile Mean	0.348	0.769	0.920	0.974	0.348	0.769	0.920	0.974
DD Estimate:								
$\beta^{(q=4)} - \beta^{(q=1)}$	-0.046*** (.010)	-0.020 (.014)	-0.014 (.013)	-0.019 (.013)	-0.020** (.008)	-0.027*** (.009)	-0.009 (.011)	-0.005 (.009)
$\beta^{(q=4)} - \beta^{(q=2)}$	-0.020** (0.009)	-0.013 (0.009)	-0.009 (0.011)	-0.019* (0.011)	-0.009 (0.007)	-0.017** (0.007)	-0.005 (0.008)	-0.003 (0.008)
$\beta^{(q=4)} - \beta^{(q=3)}$	-0.012 (0.009)	-0.005 (0.009)	0.001 (0.012)	-0.021* (0.011)	-0.007 (0.007)	-0.014** (0.007)	0.001 (0.008)	-0.008 (0.008)

Districts

11,666

11,693

District*Year*Grade
Observations

307,591

313,978

Notes. Each panel and subject represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. For each district characteristic – the proportion of district students who are either black, Hispanic or white – quartiles were created based on values from the 2007-08 school year. Districts with the lowest proportion of students, by racial/ethnic composition, are included in Quartile 1; districts with the highest proportion of students, by racial/ethnic composition, are included in Quartile 4. Proportions based on the 2007-08 school year of the population classified as black, Hispanic and white, respectively, for each demographic quartile are reported and labeled as quartile mean. All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 9. Recession Effects on Student Achievement, by District Locale

	Urban	Suburban	Town	Rural	P-value from F-Test: <i>Equal Across Locales?</i>
Panel A: Math					
RI ^{q=1} *Exposure = $\beta(q=1)$	0.019 (.012)	0.013 (.009)	0.005 (.010)	-0.018*** (.007)	0.018
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.010 (.009)	-0.000 (.005)	-0.023*** (.006)	-0.025*** (.005)	0.001
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.018** (.008)	-0.018** (.007)	-0.017*** (.007)	-0.016*** (.005)	0.994
RI ^{q=4} *Exposure = $\beta(q=4)$	-0.016 (.010)	-0.015** (.007)	-0.037*** (.006)	-0.038*** (.007)	0.035
Proportion in Locale	0.302	0.386	0.122	0.190	
DD Estimate:					
$\beta(q=4) - \beta(q=1)$	-0.035** (.016)	-0.028** (.012)	-0.042*** (.012)	-0.021** (.010)	
$\beta(q=4) - \beta(q=2)$	-0.006 (0.014)	-0.015* (0.008)	-0.014 (0.009)	-0.013 (0.009)	
$\beta(q=4) - \beta(q=3)$	0.002 (0.013)	0.003 (0.010)	-0.019** (0.009)	-0.022** (0.009)	
Districts	11,721				
District*Year*Grade Observations	308,632				
Panel B: ELA					
RI ^{q=1} *Exposure = $\beta(q=1)$	0.042*** (.009)	0.042*** (.006)	0.048*** (.007)	0.022*** (.005)	0.004
RI ^{q=2} *Exposure = $\beta(q=2)$	0.035*** (.006)	0.030*** (.003)	0.030*** (.005)	0.018*** (.005)	0.117
RI ^{q=3} *Exposure = $\beta(q=3)$	0.032*** (.006)	0.029*** (.004)	0.031*** (.005)	0.019*** (.004)	0.166
RI ^{q=4} *Exposure = $\beta(q=4)$	0.041*** (.007)	0.011* (.006)	0.030*** (.005)	0.010* (.005)	0.001
Proportion in Locale	0.303	0.386	0.122	0.189	
DD Estimate:					
$\beta(q=4) - \beta(q=1)$	-0.002 (.012)	-0.031*** (.009)	-0.018** (.008)	-0.013* (.007)	
$\beta(q=4) - \beta(q=2)$	0.006	-0.019***	0.000	-0.008	

	(0.010)	(0.007)	(0.007)	(0.007)
$\beta^{(q=4)} - \beta^{(q=3)}$	0.009 (0.009)	-0.017** (0.008)	-0.001 (0.007)	-0.009 (0.007)
Districts	11,748			
District*Year*Grade Observations	315,034			

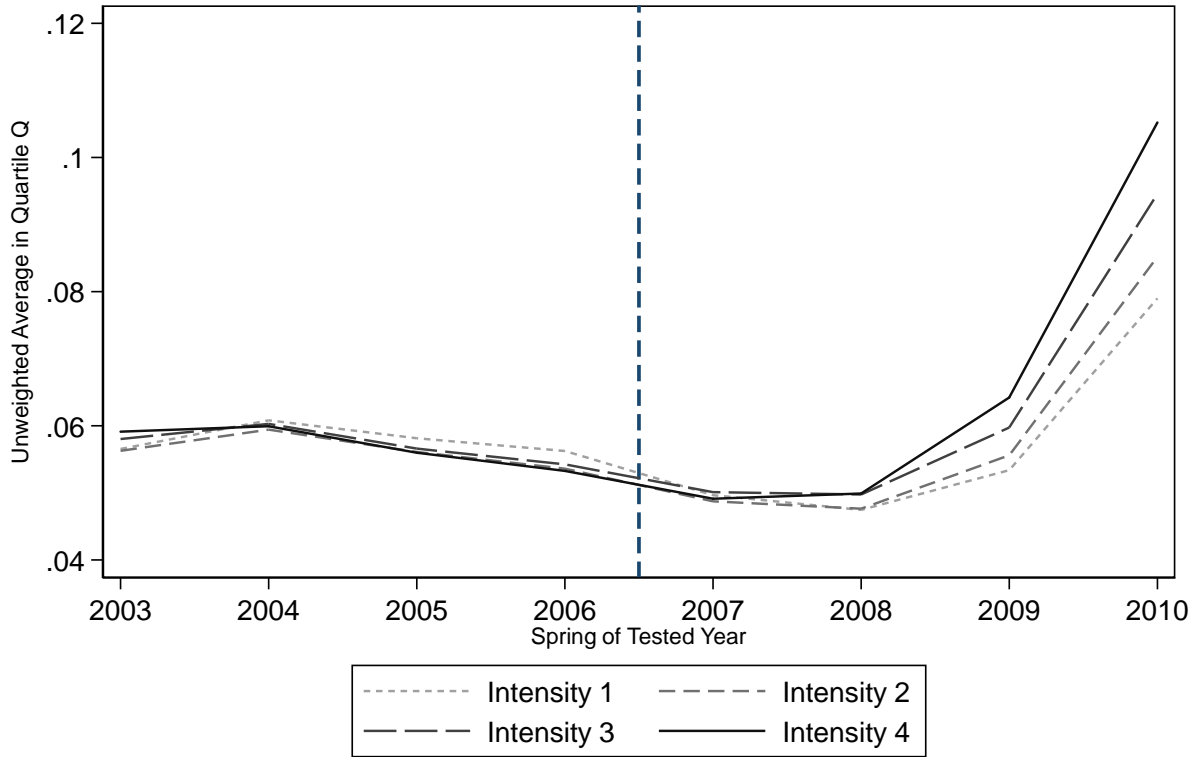
Notes. Each column (within a panel) represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. Proportion of the student population attending schools in the 2007-08 school year, by geographic locale (i.e., urban, suburban, town, rural), are reported and labeled as proportion in locale. All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Table 10. Recession Effects on Student Achievement, by Changes in School Resources

	Math			ELA		
	$\Delta Resources$ $\beta^{(q=4)-(q=1)}$	$\Delta Resources$ $\beta^{(q=4)-(q=2)}$	$\Delta Resources$ $\beta^{(q=4)-(q=3)}$	$\Delta Resources$ $\beta^{(q=4)-(q=1)}$	$\Delta Resources$ $\beta^{(q=4)-(q=2)}$	$\Delta Resources$ $\beta^{(q=4)-(q=3)}$
Panel A: Teacher Shocks						
DDD Estimate	-0.040*	-0.043**	-0.048**	-0.040**	-0.055***	-0.046***
	(0.021)	(0.021)	(0.021)	(0.019)	(0.014)	(0.015)
Districts		10,685			10,702	
District*Year*Grade Observations		281776			288044	
Panel B: Instructional Expenditure Shocks						
DDD Estimate	-0.012	-0.021	-0.027	-0.039**	-0.021	-0.038**
	(0.024)	(0.020)	(0.019)	(0.016)	(0.014)	(0.015)
Districts		11,465			11,480	
District*Year*Grade Observations		304105			310280	

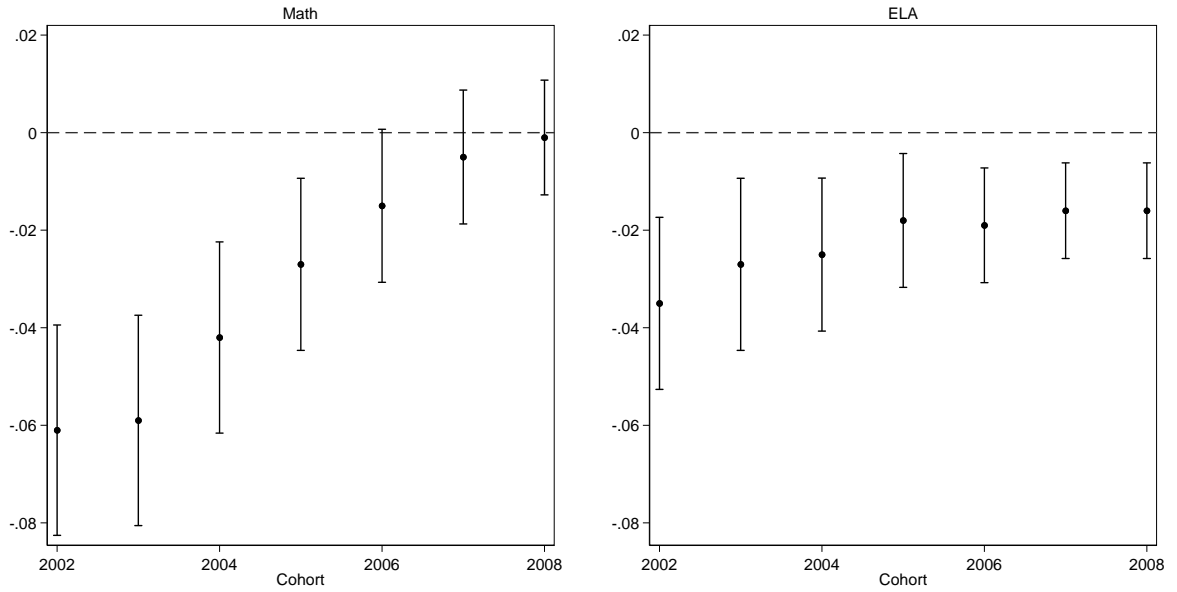
Notes. Coefficients with robust standard errors (clustered at the district level) are reported. The DDD estimates are based on estimates of equation (4) (see Table A4 for the parameter estimates upon which the DDD estimates are based). Columns (within subject) correspond to increasingly more severe school resource shocks (i.e., $\Delta Resources \beta^{(q=4)-(q=1)}$ is a more severe resource shock than $\Delta Resources \beta^{(q=4)-(q=3)}$, net of recessionary intensity). All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

Figure 1. Unemployment Rate, by Recession Intensity Quartile



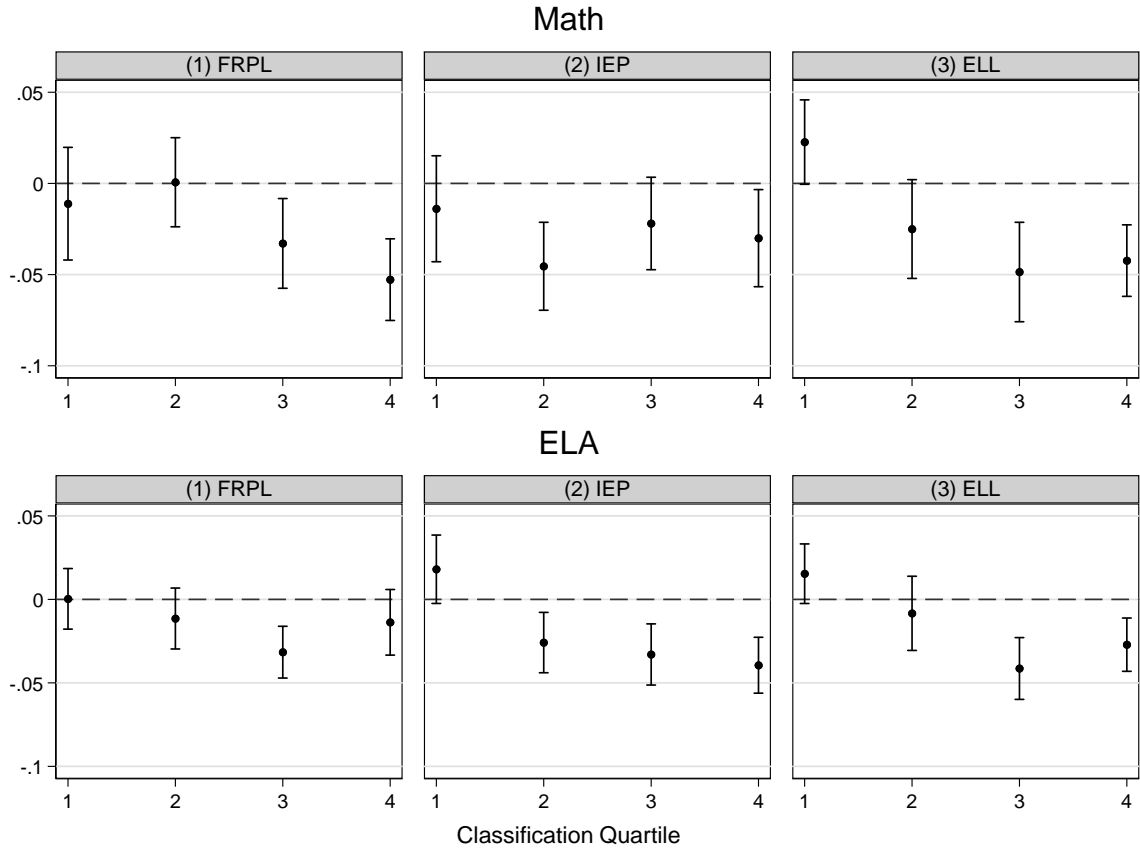
Notes. Figure maps the average unemployment rate by recession intensity quartile q , for academic years 2002-03 (i.e. Spring 2003) to 2009-10 (i.e., Spring 2010). Following Yagan (2016), recession intensity is equal to the net change in log employment for years 2003-2006 and 2007-2010 in county c .

Figure 2. Recession Effects, by Cohort (Age of Exposure)



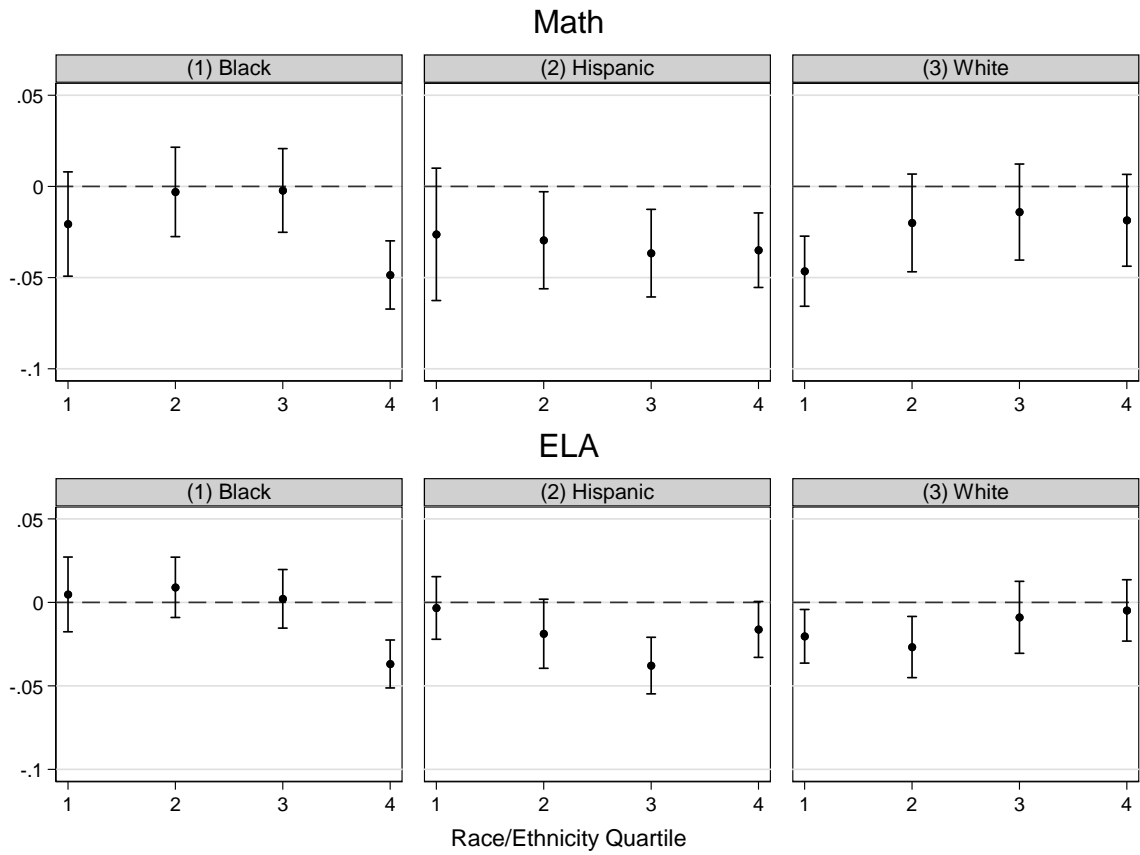
Notes. Point estimates are equal to $\beta^{(q=4)} - \beta^{(q=1)}$, and plotted for each cohort c , where cohorts are defined as Spring year t minus grade g (e.g., cohort 2002 corresponds to kindergarten cohort in year 2002). 95% confidence intervals are shown as range caps.

Figure 3. Recession Effects, by Student Characteristics



Notes. Point estimates are equal to $\beta^{(q=4)} - \beta^{(q=1)}$, and plotted for each quartile of FRPL, IEP and ELL, respectively, where quartile 1 includes districts with the lowest proportion of the either FRPL, IEP, or ELL students and quartile 4 includes districts with the largest proportion. 95% confidence intervals are shown as range caps.

Figure 4. Recession Effects, by District Racial/Ethnic Composition



Notes. Point estimates are equal to $\beta^{(q=4)} - \beta^{(q=1)}$, and plotted for each quartile of black, Hispanic and white, respectively, where quartile 1 includes districts with the lowest proportion of the either black, Hispanic or white students and quartile 4 includes districts with the largest proportion. 95% confidence intervals are shown as range caps.

Appendix

Table A1. Defining Cohorts

School Year	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
2008-09	2006	2005	2004	2003	2002	2001
2009-10	2007	2006	2005	2004	2003	2002
2010-11	2008	2007	2006	2005	2004	2003
2011-12	2009	2008	2007	2006	2005	2004
2012-13	2010	2009	2008	2007	2006	2005

Notes. SEDA test data are available for the 2008-09 through 2012-13 school years. Each cell indicates a Cohort, defined as the Spring of the school year minus the grade level. There are ten cohorts in the data.

Table A2. Exposure to Recession, by Cohort

Cohort	Exposure to Recession	Years of Achievement Data	
		Recession Period	Post-Recession Period
2001	2	1	0
2002	2	1	1
2003	2	1	2
2004	2	1	3
2005	2	1	4
2006	2	1	4
2007	2	0	4
2008	2	0	3
2009	1	0	2
2010	0	0	1

Notes. *Exposure to Recession* is defined as the number of school-age years a Cohort was exposed to the Great Recession. The Great Recession officially began in December 2007 – during the 2007-08 school year – and officially concluded in June 2009 – during the 2008-09 school year (Source: The National Bureau of Economic Research: <http://www.nber.org/cycles.html>). The *Recession Period* includes the 2008-09 school year; the *Post-Recession* period includes the 2009-10 through 2012-13 school years.

Table A3. Examining Non-Random Sorting in Response to the Recession, by Racial/Ethnic Composition

Dependent Variable	%Black		%Hispanic		%White		%Asian	
	Math Weights	ELA Weights	Math Weights	ELA Weights	Math Weights	ELA Weights	Math Weights	ELA Weights
$RI^{q=1} * Exposure = \beta^{(q=1)}$	0.004*** (.001)	0.004*** (.001)	0.001 (.001)	0.002* (.001)	-0.004*** (.001)	-0.004*** (.001)	0.000 (.000)	0.000 (.000)
$RI^{q=2} * Exposure = \beta^{(q=2)}$	0.005*** (.001)	0.004*** (.001)	-0.000 (.001)	0.000 (.000)	-0.002* (.001)	-0.002* (.001)	-0.001** (.000)	-0.001** (.000)
$RI^{q=3} * Exposure = \beta^{(q=3)}$	0.002*** (.001)	0.002*** (.001)	0.001** (.000)	0.001** (.000)	-0.003*** (.001)	-0.003*** (.001)	-0.000 (.000)	0.000 (.000)
$RI^{q=4} * Exposure = \beta^{(q=4)}$	-0.001* (.001)	-0.001** (.000)	0.000 (.000)	0.000 (.001)	-0.000 (.001)	-0.001 (.001)	0.000 (.000)	0.000 (.000)
Mean of D.V.	.171	.166	.195	.203	.565	.557	.035	.040
P-value from F-Test:								
$\beta^{(q=4)} = \beta^{(q=1)}$	0.000	0.000	0.315	0.184	0.001	0.008	0.634	0.662
$\beta^{(q=4)} = \beta^{(q=2)}$	0.000	0.000	0.639	0.898	0.102	0.324	0.018	0.013
$\beta^{(q=4)} = \beta^{(q=3)}$	0.000	0.000	0.153	0.169	0.001	0.005	0.230	0.593
Districts	11,730	11,748	11,730	11,748	11,730	11,748	11,730	11,748
District*Year*Grade Observations	308,650	315,034	308,650	315,034	308,650	315,034	308,650	315,034

Notes. Each column represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. The dependent variable in each regression is the proportion of students by race/ethnicity. Math and ELA weights reflect regression models in which the precision-weighting variable $1/\hat{\sigma}_{dgt}^2$ (where d denotes district, g denotes grade (3-8) and t denotes school year) is for math and ELA, respectively. Use of both math and ELA weights ensures that neither the math nor ELA weights (used for achievement results, respectively) result in different composition changes. Results correspond to analytic sample years, 2008-09 to 2012-13, and grades, 3-8. Control variables for these models are identical to primary specifications *except* dependent and independent variables cannot be same (e.g., for model where black composition is outcome, black composition is dropped from controls). Coefficients statistically significant at the *10%, **5%, and ***1% levels.

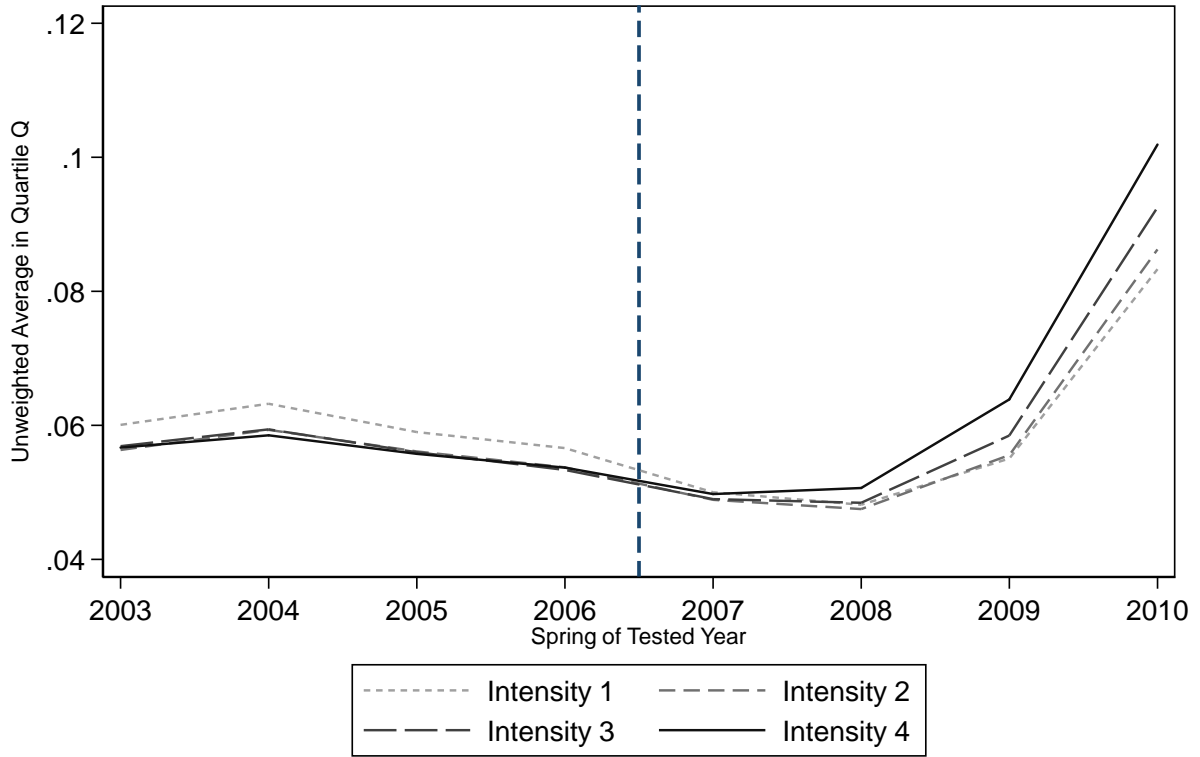
Table A4. Potential Mechanisms: Changes in School Resources

	Math				ELA			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Panel A: Teacher Shocks								
RI ^{q=1} *Exposure = $\beta(q=1)$	0.022** (.012)	-0.006 (.012)	-0.003 (.011)	0.019 (.014)	0.041*** (.010)	0.029*** (.007)	0.040*** (.008)	0.054*** (.009)
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.013*** (.006)	0.005 (.006)	-0.003 (.008)	-0.022*** (.009)	0.024*** (.005)	0.040*** (.004)	0.037*** (.006)	0.020*** (.005)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.003 (.007)	-0.002 (.006)	-0.020*** (.008)	-0.011 (.007)	0.029*** (.006)	0.037*** (.005)	0.031*** (.005)	0.023*** (.007)
RI ^{q=4} *Exposure = $\beta(q=4)$	0.004 (.008)	-0.021** (.009)	-0.014* (.008)	-0.039*** (.006)	0.029*** (.012)	0.031*** (.006)	0.032*** (.006)	0.001 (.005)
Quartile Mean	0.234	0.032	-0.060	-0.291	0.234	0.032	-0.060	-0.292
Districts		10,685				10,702		
District*Year*Grade Observations		281,776				288,044		
Panel B: Instructional Expenditure Shocks								
RI ^{q=1} *Exposure = $\beta(q=1)$	0.018 (0.011)	0.006 (.010)	-0.005 (.010)	0.012 (.013)	0.045*** (.008)	0.043*** (.006)	0.027*** (.008)	0.044*** (.008)
RI ^{q=2} *Exposure = $\beta(q=2)$	-0.009 (.007)	-0.009 (.006)	-0.007 (.008)	-0.017 (.010)	0.035*** (.005)	0.034*** (.004)	0.032*** (.005)	0.018*** (.007)
RI ^{q=3} *Exposure = $\beta(q=3)$	-0.012 (.007)	-0.019*** (.007)	-0.019*** (.007)	-0.017* (.010)	0.030*** (.006)	0.031*** (.005)	0.029*** (.004)	0.022*** (.006)
RI ^{q=4} *Exposure = $\beta(q=4)$	-0.016 (.014)	-0.018*** (.007)	-0.023*** (.006)	-0.033*** (.008)	0.044*** (.009)	0.024*** (.007)	0.025*** (.005)	0.004 (.006)
Quartile Mean	0.195	0.038	-0.051	-0.216	.234	.032	-.060	-.292

Districts	11,465	11,480
District*Year*Grade Observations	304,105	310,280

Notes. Each subject (within a panel) represents a separate regression. Coefficients with robust standard errors (clustered at the district level) are reported. Panel A (Teacher Shocks) and Panel B (Instructional Expenditure Shocks) are equal to $\Delta Resources_d = \left[\ln \left(\frac{R_{d,2010}}{R_{d,2007}} \right) - \ln \left(\frac{R_{d,2006}}{R_{d,2003}} \right) \right]$, where R indicates either counts of teachers or real (\$2010) total instructional expenditures in district d during spring of school year t (e.g., 2010 is the 2009-10 school year). $\Delta Resources_d$ is disaggregated into q quartiles, as in $Recession_c$ from Equation (1). Districts with the smallest net log change in either teachers or instructional expenditures (lowest resource shocks) are included in Quartile 1; districts with the largest net log change (largest resource shocks) are included in Quartile 4. The average net log change is displayed in the row labeled Quartile Mean. All regressions control for district-level demographics (total K-12 enrollment per teacher (i.e., class size) and the proportion of students eligible for FRPL) and resource characteristics (real total revenue per pupil and real per pupil instructional expenditures), indicators for geographic locale of the district (urban, suburban, rural, town), district*grade-level racial composition measures (proportion of students in grades 3-8 who are white, black and Hispanic), district fixed effects, year fixed effects and grade fixed effects. Coefficients statistically significant at the *10%, **5%, and ***1% levels.

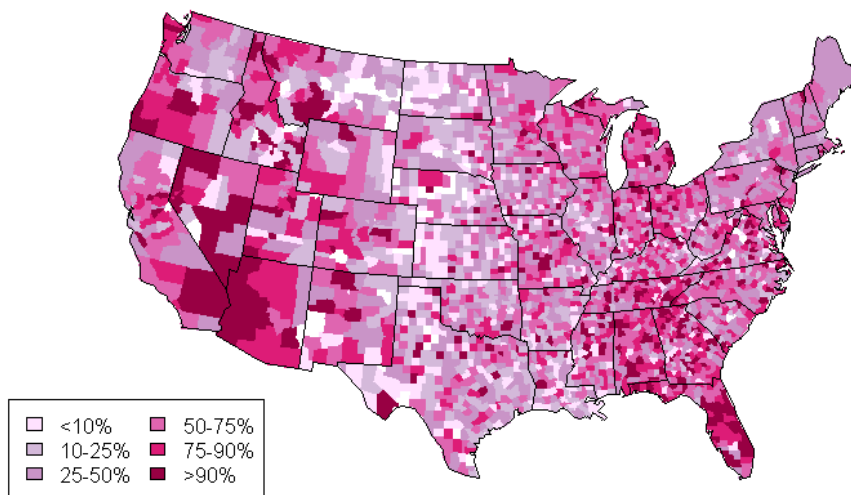
Figure A1. Unemployment Rate, by Recession Intensity Quartile (alternative pre-period)



Notes. Figure maps the average unemployment rate in recession intensity quartile q , for academic years 2002-03 to 2009-10 using an alternative pre-recession period – Spring 2001 to Spring 2004. Recession intensity is equal to the net change in log employment for Spring years 2000-2003 and 2007-2010 in county c .

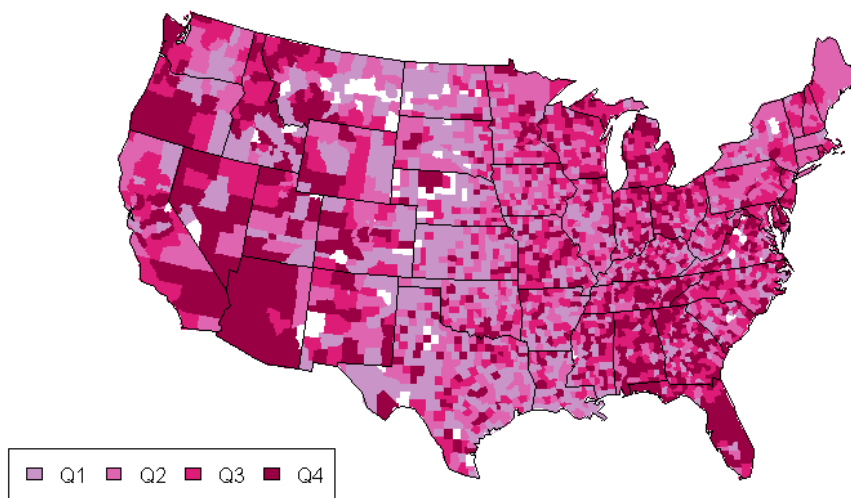
Figure A2. Distribution of Recession Intensity

Net Log Employment Change (2010-2007) - (2006-2003)



(a) Standardized Recession Intensity

Recession Intensity Quartiles



(b) Recession Intensity Quartiles

Notes. Panel (a) shows $Recession_c$ standardized to be $\sim N(0,1)$ and scaled so that higher values correspond to less employment growth. Panel (b) shows quartiles of $Recession_c$, again scaled so that higher values correspond to less

employment growth. Sample limited to analytic sample (non-missing achievement and independent variables). For visualization purposes, values are top and bottom coded, meaning that values outside the 1st and 99th percentiles are set equal to the 1st and 99th percentile values, respectively. Figure is comparable to Yagan (2016) who plots net log employment changes for commuting zones.