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The Effects of Local Employment Losses on Children's Educational Achievement

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October 8, 2009

The authors would like to thank Dania Frank for her outstanding research assistance and Dorothyjean Cratty for her expert analytical support. They gratefully acknowledge the support of the Spencer Foundation, the Russell Sage Foundation, and the Smith Richardson Foundation. Ananat acknowledges the support of The Brookings Institution; Gibson-Davis acknowledges the support of the W.T. Grant Foundation. Helpful comments were provided by members of the Smith Richardson research team at Duke University and by participants in the Russell Sage-Spencer Foundation Conference on Social Inequality and Educational Disadvantage.

Abstract

Given that even temporary income losses are strongly correlated with persistent negative outcomes for children (Duncan and Brooks-Gunn 1994), the current US economic crisis raises the question of what effect we can expect large-scale job destruction to have on child well-being. We examine this question by combining data on plant closings and layoffs in all 100 North Carolina counties over the period 1997 to 2007 with data on test scores for all public-school 8th-graders in the state. We find that job destruction within a county lowers the test scores of children from low-SES but not from high-SES families, which is consistent with an emerging consensus in the literature on individual-level job loss (Oreopoulos, Page and Stevens 2008; Stevens and Schaller 2009). Exploring this result, it appears that the lower test scores are not the product of structural changes, such as reduced school resources, as federal funding per student typically increases and teacher turnover falls while student turnover remains constant after plant closings. Evidence is also inconsistent with a model of strong peer effects or strategic changes in investment in schooling. Instead, our results suggest that effects within families most likely account for much, but probably not all, of the observed negative impacts.

Introduction

As the United States closes out the first decade of the 21st century, it is experiencing its worst economic crisis since the Great Depression. Rising unemployment and associated increases in poverty have highlighted the importance of understanding the linkages between economic downturns and child well-being, as even temporary income losses are strongly correlated with negative outcomes for children (Duncan and Brooks-Gunn 1997).

Identifying the causal effects of economic losses on children, however, is difficult, as in most instances there are likely to be unmeasured or unobserved characteristics that both affect a given family's financial status and affect that family's well-being. For example, parents with low unobservable skills may be both less likely to maintain employment and more likely to have children with low levels of school success than parents with higher skills. Moreover, even instrumenting for parental job loss may miss effects of economic crises on children that come through channels other than parental unemployment, such as increased stress among parents and teachers from a poor economic climate, declines in the tax base that reduce school resources, or spillover effects in the classroom from peers whose parents lose jobs.

In this paper, we avoid the problems of endogeneity and of an overly-narrow focus on parental job loss by examining the relationship between community-level job losses induced by plant closings and the community's student test scores. Using plausibly exogenous variation caused by plant closings permits us to identify the causal effect of an economic downturn on students overall and on vulnerable subgroups of students in particular, and can provide insight to policy makers seeking solutions to cope with the effects of the current economic crisis.

We use data from North Carolina, which has experienced significant ongoing job losses due to pressures from globalization that began well before this most recent downturn. Over the past twenty years, the furniture and textile industries, once important foundations of the state's

economy, have largely collapsed, and newer economic drivers such as microchip manufacturing have been subject to significant fluctuations as well. In this paper we link information on plant closings and lay-offs occurring in each county in North Carolina to information on the end-of-grade test scores of 8th-graders in each county over the period 1997 to 2007. In addition to identifying the reduced-form effect of closings on test scores, our data enable the exploration of many potential mechanisms that allow us to peek inside the “black box” to determine *how* community economic losses affect children.

We find that community-level job losses lower the test scores of children from low-SES but not from high-SES families, which is consistent with an emerging consensus in the literature on individual-level job loss (Oreopoulos, Page and Stevens 2008; Stevens and Schaller 2009). This finding passes a variety of specification tests. Exploring this result, it appears that the lower test scores are not the product of structural changes, such as reduced school resources, as federal funding per student typically increases and teacher turnover falls while student turnover remains constant after plant closings. Evidence is also inconsistent with a model of strong peer effects or strategic investment effects. Instead, our results suggest that effects within families most likely account for much, but probably not all, of the observed negative impacts.

Background

A broad consensus now exists that plant closings can be viewed as exogenous shocks to workers and communities when conditioning on prior characteristics (Jacobson, LaLonde and Sullivan 1993; Stevens 1997) and that effects on workers and communities subsequent to closings can therefore be interpreted as causal effects of job loss. Literature in this area has tended to concentrate either on the effect of community-level job losses (the total number of jobs

lost in a community) on community-wide economic outcomes such as levels of employment or welfare receipt, or has looked at the effect of an individual-level job loss (whether the household head in family loses a job due to a closing, regardless of how many others in the community are affected) on family-level outcomes such as income, parenting practices or children's test scores. We, instead, examine the effect of community-wide job losses (the number of jobs lost in the community) on community-wide measures of children's achievement, which allows us to identify effects on children that do not come through their parents' employment status. In this section we discuss the community-level and individual-level literatures on the effect of job loss, and use them to generate hypotheses on why community-wide job losses might affect aggregate levels of child well-being.

Evidence on community-level losses

Within economics, several papers have measured the causal effects of job loss on community-level employment, earnings, and public assistance receipt. A set of studies by Black, McKinnish, and Sanders (2003; 2005a, b) examining booms and busts in the steel and coal industries in the 1970s and 1980s found that downturns led to lower employment not only within but also outside of the initially affected industries. Closures resulted in lower aggregate earnings in affected counties and to higher rates of receipt of Disability Insurance and Aid to Families with Dependent Children. Both lower income and higher rates of public assistance receipt might augur worse outcomes for children, including among children whose parents were not directly affected by a plant closure but were affected by related job loss in other industries. Bartik (1993) finds that the employment and wages of minorities and low-skilled workers are particularly impacted by changes in the rate of local job growth, which raises the possibility that children from disadvantaged families in particular may have lower test scores in the wake of job

losses.

Other research has examined the effects of relative job losses on community characteristics, such as property values. Greenstone and Moretti (2004) find that, when comparing counties that were finalists to receive a new plant, the county that did not win the plant experienced lower property value growth than did its winning counterpart. Lower property values imply a lower overall quality of life in a community, but do not identify in what specific way(s) residents are worse off. Greenstone, Hornbeck, and Moretti (2008) explore wages and employment and find evidence for both as partial mechanisms for the difference in property values. However, it is plausible that a worse educational environment for children is another cause of lower property values. Moreover, decreased property values by themselves can cause a decline in the level of financial resources and therefore the quality of a community's public education system (Ludwig and Bassi 1999).

Finally, qualitative work has found increases in community-level stress from large local firm shutdowns. Zippay (1991) details how displaced steelworkers in a Pennsylvania community were required to rely on family, friends, and neighbors for economic and social support. If enough people in a community experience job loss after a plant closes, it is quite likely that the aggregate level of stress may increase among family, friends, and neighbors, and thereby impact families that do not directly experience unemployment. In addition to increases in parent stress, teacher stress might also increase, altering the educational environment of schools.

Several pieces of evidence suggest that there may be “silver linings” for communities from plant closings, however. The studies of steel and coal communities by Black et al (2005a, b) find that downturns led to reductions in school dropout, as people looked to education to

improve their job market prospects. Increased parental education might portend better outcomes for children (Oreopoulos, Page and Stevens 2006), and older children may also respond to a changing job market by investing more in their own educations. In addition, decreased opportunities in the local private labor market may increase teacher retention, which has been linked with higher student achievement (Rockoff, 2004).

Evidence on individual-level losses

The most immediate individual-level effect of losing one's job through a plant closing is unemployment. Researchers have found that unemployment has strong links to individual well-being in many domains, including not only economic well-being but also physical health (Sullivan and von Wachter 2009), psychological health (McKee-Ryan et al. 2005), and one's sense of satisfaction and accomplishment (Blustein 2008). Job loss also leads to decreased earnings over the longer term, because people who lose their jobs due to industry downturns must start over in new firms and new industries (Jacobson, LaLonde and Sullivan 1993; Stevens 1997).

Individual unemployment is associated with higher levels of parental depression and anxiety (Jones 1988; Conger and Elder 1994; McLoyd et al. 1994), and parental mental health has been found to have strong links to child adjustment and school achievement (Elder et al. 1995; McLoyd 1998). In particular, recent research has shown that parental unemployment due to plant closings has negative effects on children's grade completion (Stevens and Schaller 2009), test scores (Rege, Telle and Votruba 2007), and later human capital acquisition (Oreopoulos, Page and Stevens 2008). Even after transitioning out of unemployment, permanently lower parental earnings can affect children, insofar as parents' ability to provide material resources has been found to be critical to child well being and in particular to school

achievement (Dahl and Lochner 2008).

Hypotheses

The consensus that plant closings cause negative impacts on communities beyond just individual impacts on those who were formerly employed at the plants (through related job losses, declining property values, and the like), when combined with the consensus that parental job loss harms children’s outcomes, suggests there may be multiple impacts of community plant closings on aggregate child academic achievement. In this paper we test this question by examining whether community-level job losses induced by firm closings¹ cause decreases in test scores among local eighth-graders.

We hypothesize that plant closings may affect test scores both through lower achievement of children whose parents lose jobs and through additional community-level mechanisms. We do not, therefore, expect that the relationship between community job losses and community average test scores will be simply the relationship between individual-level job loss and child tests scores identified in earlier papers (Oreopoulos, Page and Stevens 2008; Stevens and Schaller 2009) scaled by the size of the plant closing in relation to the size of the community. Whether the relationship at the community level is more or less negative than the relationship at the family level depends on whether potential negative impacts of job losses on communities (declining tax base, increased stress) or potential “silver lining” impacts (increased teacher retention, increased expected returns to education) dominate.

Our dataset does not allow us to observe whether each child has experienced job loss at the family level; however, using demographic information on children we are able to identify

¹ Our measure of job loss includes both closings and layoffs, but for ease of explication, we refer to both types of losses as closings. Robustness checks indicated that our results do not differ by the type of job loss considered.

subgroups of children whose families are likely to have been directly impacted by job losses and compare their outcomes to those of demographic subgroups whose families likely did not individually lose jobs. In this way we are able to gauge the extent to which community-level job losses affect members of the community both who do and who do not experience individual losses. Further, we build on previous research by examining a variety of potential community-level mechanisms for the causes of changes in child outcomes. For example, we test how school financial and teacher resources change after local plants close. We look for changes in peer composition after closings, and for peer effects through spillovers from affected to unaffected groups of children. We test for impacts through strategic educational investments by examining whether children respond more strongly to changes in employment within their own gender.

Data

Data for this paper come from three sources. The first source is student achievement data from the North Carolina School Administrative Records database. This database contains detailed information for all 115 public school districts in North Carolina. Data are available at the district, school, teacher, and student levels, and include a wide variety of measures, including school demographic composition, teacher performance and experience, and student achievement. These data are collected by the North Carolina Department of Public Instruction and housed at the North Carolina Education Research Data Center (NCERDC) at Duke University. Data are available from 1997 to 2007, with additional waves being added as they become available. Table 1 presents demographic data on students, including race and gender composition. Table 1 also reports a measure available in the data that allows us to proxy for students' socioeconomic background: the highest education level either of their parents has achieved. While the education

categories vary from year to year in the data, it is always possible to distinguish parents with more than a high school education from parents who are high school graduates or dropouts. Just over half of North Carolina students (56.4%) fall into the latter category.

The measures of achievement data that we use are end-of-grade (EOG) tests in reading comprehension and math. Tests are taken by all 8th graders in North Carolina public schools. EOG tests in reading comprehension measure the ability to demonstrate understanding of a passage and knowledge of vocabulary. EOG tests in math measure proficiency in five areas: number and operations, measurement, geometry, data analysis and probability, and algebra. We chose to focus on tests taken by 8th graders because such tests are unlikely to be affected by dropout rates. Additionally, unlike tests taken in later grades, these tests are required of all 8th graders, regardless of their curriculum or track. Because the scoring of tests has varied over time, we standardize each year's scores to have a mean of 0 and a standard deviation of 1. We then take the mean score within each of 100 counties for each of 11 years. We use data from 1,058,077 tests in reading comprehension, and 849,076 tests in math. Table 2 presents raw test score summary statistics for the universe of students. Students with at least one parent who has more than a high-school degree average math and reading scores nearly one standard deviation higher than students whose parents are both high school graduates or dropouts.

The second data set is an array of publicly available county-level time-varying characteristics. Data provided at the county level include: size of the working-age population (US Census Bureau); unemployment rate (US Bureau of Labor Statistics); and tax revenue per capita (NC Treasury). We also present county-level schools data; most of the 100 counties in North Carolina contain exactly one school district, and for the handful of counties that contain more than one school district, we make county-level measures using pupil-weighted average of

district characteristics. The schools measures, all from the NCERDC database, include: the one-year teacher turnover rate, student poverty rate, per pupil expenditures, student racial composition, and within-district racial segregation.² Summary statistics for these measures are presented in Table 3, along with county-level averages of raw reading and math test scores.

The third data set is the Factory Closings Database, an in-house database that utilizes industry information obtained from the North Carolina Employment Security Commission. The Employment Security Commission provides information on any business that shuts down or lays off workers. Based on this information, we have constructed, for all 100 counties and for the years 1997-2007, a database that includes the company name, the type of business being affected (according to the North American Industry Classification System), whether the business is closing or laying off workers, the number of workers affected, the date of closing, and the reason for the closing/layoff (e.g., plant relocation, consolidation to one branch, etc). While the economics literature has typically treated job losses and job gains as parallel processes, we focus on losses, because policy concerns center on remedying harm caused by unemployment, and behavioral economics research suggests that losses may have stronger impacts than gains.

By combining the NAICS code associated with the closing/layoff with data from the decennial US Census, we have identified the national age, gender, race, and skill composition of the industry in which workers lost jobs; this information allows us more precision in matching job losses to students whose parents' earning prospects are likely to have been impacted by the event. We compile these job losses at the county level by quarter, and calculate the share of all jobs in the county that are lost in that quarter due to the closing.

Good variation exists in this measure both across counties and over time, as illustrated by Figures 1 and 2. Figure 1 displays the maximum share of jobs lost to closings in a quarter in each

² Calculated by the authors from school-level racial composition using the formula for a standard dissimilarity index.

county over the period under observation, 1997 to 2007. Losses range from zero for three small farming communities to 6.9 percent in Allegheny County, where a large air conditioning plant closed. Other large plant closings include a textile plant in Cabarrus County (jobs lost to 4.7 percent of the working-age population) and a poultry farm in Chatham County (3.4 percent). Figure 2 displays the variation within and between years and counties in the intensity of job losses. Job losses were generally most intense prior to 2003 when textile, tobacco, and manufacturing were experiencing severe declines, though they continued throughout the study period.

Our data on closings and layoffs strongly predict unemployment. Figure 3 displays graphically the relationship between overall losses at the state level and North Carolina's residual unemployment relative to national trend over time; the two lines co-vary visibly. Within counties, a job loss impacting one percent of a county's working-age population (age 16-64) leads to an increase in unemployment of 0.86 percent (standard error=0.095) the following quarter; the effect fades in the next quarter, causing an increase in unemployment relative to baseline of 0.73 percent (standard error=0.075). It continues to fade subsequently.

Methods

We estimate the equation:

$$Score_{cy} = \phi JobLoss_{cy} + X_{cy} + \theta_y + \theta_c + \theta_c * y + \theta_c * y^2 + \varepsilon \quad (1)$$

where $Score_{cy}$ is the average normalized test score for county c in year y , and $JobLoss_{cy}$ represents the number of jobs recently lost to closings and layoffs for that county c in year y , as discussed in more detail below. X_{cy} is a vector of county-year specific controls, and includes: the percentage of the district that is African-American, percentage that is Hispanic, percentage that is

Asian, and percentage that is in poverty. All models also include year indicators, county indicators, and linear and quadratic county time trends (county indicators interacted with year and year squared). In some regressions, we estimate a variation on equation (1) that replaces $Score_{cy}$ with another county-year outcome, such as teacher turnover or tax revenue per capita.

It is ultimately arbitrary how to define “recent” when creating the measure $JobLoss_{cy}$, the number of jobs recently lost in the county. One option is to include separate measures of job losses that have occurred in each period prior to the test (all the way back to the beginning of the panel), but including multiple controls for job losses in different periods would result in a loss of statistical power. Instead, for elegance and clarity, our preferred specification includes a single measure of recent losses (although using up to four measures provides similar results).

In creating a single measure, there are again multiple possible ways to aggregate losses. At one extreme, we could model total job losses as the sum of losses that have occurred since the beginning of the panel; handling the data that way would mean that students in later years mechanically get a stronger “treatment” than those in earlier years. At the other extreme, we could model student test scores as affected only by job losses that have occurred within the past quarter, and put zero weight on any losses that occurred earlier. As a compromise between these two extremes, we model the impact of job losses as decaying exponentially over time. The dependent variable for the percent of a county’s working age population affected by plant closings in test year y (defined as ranging from year 1, for 1997, to year 11, for 2007) is the sum of job losses in each quarter multiplied by that quarter’s recency weight:

$$JobLoss_{cy} = \sum_{q=1}^{4y} W_q L_{cq}$$

where q is the test quarter (defined as 1997 Q3 =1, 1997 Q4 =2, ..., 2007 Q2 =44), L_{cq} is job losses as a percent of working-age population in county c in quarter q , and W_q is the recency weight for quarter q . The recency weights are derived using an exponential decay function based on a half-life of one quarter. We use this half-life so that job losses in spring—just before testing—are given greater weight in our regression than those occurring the previous fall. The half-life formula for exponential decay is

$$W_q = e^{-\frac{p \cdot \ln(2)}{h}},$$

where p is elapsed time (here, in quarters between the closing and the test date) and h is the half-life (here, one quarter). For our purposes, then, $W_q = e^{-0.693(q - q_{event})}$, where q is the test quarter and q_{event} is the closing quarter. As an illustrative example, if a county with 100,000 adults aged 16 to 64 experienced exactly one job loss in the year prior to the test, and that job loss affected 1000 individuals, and occurred in May of the test year, then the value of JobLoss for that county in that year would be 1000/100,000, or 1.00%.

In some cases, we use an alternate measure of job losses that represents the share of losses attributable to a given demographic group g :

$$JobLoss_{gcy} = \sum_{q=1}^{4y} W_q \left(\sum_i share_g_i L_{icq} \right),$$

where g is a population subgroup such as high school graduates, women, African-Americans, or 16- to 20-year-olds. $Share_g_i$ is group g 's national share of employment in the industry, i , that experienced the closing. When using this measure, if the county in the above example experienced the loss in an industry that employs 50 percent women and 30 percent African-

Americans nationally, then *JobLoss* would equal 0.50% for women and 0.30% for African-Americans.

Estimating φ , the effect of job losses on test scores (or another outcome), using county and year fixed effects and county-specific time trends produces coefficients free of bias due to unobserved time-invariant effects and nonlinear trends. This means the estimated effects are not mistakenly capturing the fact that counties with above average closings may have below average scores, or that both closings and scores are increasing over the sample period and trending faster in some counties. For example, an estimate of φ of -0.1 when looking at the effect of normalized job losses on normalized reading scores would imply that a county that experienced a job loss to 1% of its working-age population in the previous year had reading scores 1/10 of a standard deviation lower than would otherwise be expected given that county's typical test scores and recent trend in scores.

But while controlling for these unobserved effects removes the county- and year-specific components from the error term, it is reasonable to expect some arbitrary contemporaneous and/or serial correlation in the remaining idiosyncratic errors that could bias the standard errors around the estimate of φ . For instance, it is likely that residuals in a given county are correlated over time, or that plant closings in one year may induce further plant closings in the next year—making prediction errors in one period correlated with those in another. Following Stock and Watson (2006), we correct for these correlated errors using a county-level cluster-robust variance estimator, which produces appropriate confidence intervals around estimates of φ .

Results

Table 4 reports the results from estimating equation (1) with $Score_{cy}$ as the outcome. When estimating the relationship of job losses to county average test scores across the entire population of students, the estimates are negative but small and not statistically significant. However, separating students by the education level of their parents indicates that those whose parents have a high school diploma or less have significantly lower scores after a job loss. A loss of jobs to one percent of the county's working-age population in the previous quarter leads to a significant decline in both math and reading scores of 2.4% of a standard deviation. These effects are even stronger when that one percent of jobs are predicted to be lost to county residents with a high-school diploma or less: such a loss leads to a significant decline in reading scores of 4.2% of a standard deviation and a marginally significant decline in math scores of 3.6% of a standard deviation. By contrast, children whose parents have more than a high school diploma experience small and insignificant, though also negative, test score impacts from job losses. This is not simply because losses are less likely to affect their families; a one-percent job loss that is predicted to occur to educated workers also has non-significant effects. Because of this finding that job losses disproportionately impact the outcomes of disadvantaged children, which are consistent with the previous literature on impacts of job loss (Oreopoulos, Page, and Stevens 2008; Stevens and Schaller 2009), we concentrate the rest of our analysis of test scores on children from low-education families.

Among those whose parents have a high school diploma or less, the effects of a loss of jobs to one percent of the population does not differ by student gender: both boys and girls experience math and reading decreases of roughly 2.4% of a standard deviation, although estimates become less precise when the sample is split. Similarly, the effects of job losses to men or to women are indistinguishable from each other; there is no evidence that losses to

female-dominated industries have a different impact on test scores than do losses to male-dominated industries, or that children are more sensitive to job losses within their gender.

By contrast, there is evidence that some minorities may be particularly impacted by job losses, and that students are more sensitive to job losses predicted to occur to members of their own ethnic group. While, again, results become less precise when the sample is split by race and ethnicity, for all groups the point estimates are much greater for own-race/ethnic job losses than for overall losses. For non-Hispanic whites the estimates are one-third larger, for African Americans they are three to five times larger, and for Hispanics they are about ten times larger. Overall, despite the lack of precision, the trends are quite clear that job losses are harmful to educational achievement, particularly to disadvantaged groups: 31 of the 32 coefficients in Table 4 are negative, one-third are statistically significant, and estimates are larger for students from less-educated families and families of color.

Table 5 presents a variety of specification tests of these results. The top panel of Table 5 shows the results of including separate measures of job losses over each of the last four quarters rather than a single composite measure on the sample of low-SES students. The results are consistent with our main results: a joint F-test for the significance of all four quarters is statistically significant for both reading ($p\text{-value}=.013$) and for math ($p\text{-value}=.025$); further, for both reading and math the effect is strongest in the first quarter and fades subsequently, which is supportive of the model of exponential decay used in our preferred specification.

The middle panel of Table 5 presents a check for whether our main results are driven by migration of high-performing low-SES students out of counties after closings. We match each student to the county in which they were first observed—usually in third grade—and use closings in that county during eighth grade to predict students' eighth-grade test scores. While

this test allows us to avoid the possibility that changes in county-level test scores shuffling of students, it necessarily introduces measurement error, as any students who moved counties between third and seventh grade were not actually exposed to the closings to which we match them. Using closings in the county in which students were originally observed as expected increases measurement error, increasing the standard errors of our estimates. However, the coefficients attenuate only slightly: even using original county of residence, we find that a job loss to one percent of that county's residents leads to about two percent of a standard deviation decline in both math and reading scores. This check gives us confidence that our main results are not driven by shuffling of students between counties but rather by treatment effects of local closings on individual students' test scores.

The bottom panel of Table 5 presents a falsification check in which we use next year's job losses to predict current test scores. Significant estimates from this regression would cast doubt on our identifying assumption that job losses can be viewed as exogenous shocks to communities; instead, such results would suggest that counties that experience closings already had differential trends in test scores. However, the estimates are very small and statistically insignificant, and the estimate on math scores is not in the expected direction. These estimates lend support to the assumption that changes in test scores do not occur to counties until after closings occur, and hence the relationship between job losses and test scores can be interpreted causally.

Having validated our finding that job losses cause declines in test scores, in Table 6 we examine the extent to which these declines may be attributable to changes in the school environment. Because many structural aspects of schools only change on a school-year basis, we also estimate the effects of last year's recency-weighted job losses on this year's school

environment. Overall, among the 100 counties in North Carolina there is very little change in the observable school environment. Per-pupil expenditures actually increase marginally after a job loss, driven by an increase in federal funding (results not shown), percent minority in the schools falls slightly, and teacher turnover declines significantly the next year.

To parallel our analysis of the subgroup of children from low-education families, we examine the subgroup of counties with high proportions of students from low-education families. It is plausible that, since the harm from job losses is concentrated among disadvantaged students, structural losses to schools lead to this harm but can be identified only through subgroup analysis of schools with concentrated disadvantaged populations. The “disadvantaged” subsample in Table 5 consists of 34 counties (374 observations) in which at least two-thirds of the students come from low-education backgrounds. While we do find more significant changes in the characteristics of schools in this subsample than in the overall sample of schools (7 of 12 relationships are statistically significant, compared to 3 of 12 in the overall sample), these relationships are not necessarily in the direction of increased vulnerability.

County per capita tax revenues decline in the year of the job loss in disadvantaged districts, but recover by the next year. To the extent that balanced budget rules require tax hikes in the case of declining revenue, it is possible that this result represents an increase in tax burden for families. However, it does not appear that any of the loss in revenue impacts school financing. To the contrary, per-pupil expenditures significantly increase in both the year of the loss and the following year, by about 1 percent, a result driven by increased local, state, and particularly federal funding. Similarly, teacher turnover in disadvantaged counties falls a highly significant 3 percent in the year after the job loss, perhaps reflecting increased retention of

teachers who, faced with a better local economy, might otherwise have left teaching for another field.

It also does not appear that in the disadvantaged counties job losses lead to an exodus of those with better prospects, as enrollment is stable. Moreover, percent minority falls slightly relative to trend, driven by a decrease in Hispanic students (result not shown). As Hispanics are a new and rapidly growing group in North Carolina, it is likely that this result represents decreased in-migration by a mobile population that is, according to Table 4, particularly sensitive to job losses; however, such a change is likely to dampen the decline test scores rather than cause it. Finally, disparities in racial composition between schools within a disadvantaged county fall after a job loss; thus it does not appear that falls in test scores among students of color reflect declining access to the same schools as white students after a job loss.

Discussion

Our subgroup analysis and our analysis of potential county-level mechanisms for the decrease in test scores among disadvantaged students, while not conclusive, are suggestive of the likelihood of a variety of pathways from job losses to decreased test scores. These include: peer and teacher effects, either compositional or behavioral; school district changes in financial resources; child responses to changes in future job opportunities; as well as direct effects from parental job loss.

Peer effects post-job loss could decrease test scores in one of two ways. First, job loss to some children's parents could cause them to act out in school (Kalil and Ziol-Guest 2008) which can disrupt the learning of other students (Figlio 2003). Second, some students might migrate out of the area or cease to migrate in; peer effects of migration will be negative if high-achieving

students become a smaller portion of the local population (Imberman, Kugler and Sacerdote 2009). However, we do not find evidence consistent with either channel. We observe little change in student composition post-job loss, and population declines are observed only among minority groups whose test scores are below average, which if anything should tend to increase test scores among remaining students. Moreover, school-level racial segregation declines post-job loss, leading to increased exposure of minority students to higher-achieving white students but nonetheless to decreases in achievement among those minority students. It is possible that behavioral changes within existing peers lead to lower test scores; since children of high-education parents seem relatively unaffected by job losses, however, there must be some mechanism by which harm from misbehaving peers is concentrated among already-disadvantaged children.

Teacher effects post-job loss could also decrease test scores either through changes in composition or through changes in teacher behavior. The stability or decrease in teacher turnover that we observe would typically imply an improvement in test scores (Rockoff 2004). However, the marginal teacher who remains in her job due to a downturn may be of lower quality than the typical teacher with her level of experience; if these teachers are strongly negatively selected, it is possible that their retention has perverse effects on students. Changes in teacher behavior may also be a cause of the decrease in test scores, if teacher stress increases due to changes in the economic environment such as the unemployment of family and friends. However, since children from high-education backgrounds do not experience worsened test scores, any such teacher-stress effects must either be in some way directed toward disadvantaged students, or else disadvantaged students must be particularly vulnerable to changes in teacher behavior.

Decreases in school district funding do not appear to be the cause of lowered test scores, as per pupil expenditures actually increase. These increases are driven by a boost in federal funding, perhaps in response to increased need in the community. Nonetheless, the increased spending does not prevent negative effects from downturns, suggesting either that compensatory funding is not effective (Hanushek 2003) or that the level of increase observed is too small.

Children's test scores might also decrease because of a change in future job market opportunities that either lowers the return to education or creates discouragement among a given demographic group. However, the fact that losses to high-education workers have little impact on test scores, and the fact that students do not respond differentially to job losses among their own gender, raise doubts about this mechanism, at least among 8th-graders. Such a mechanism may be more important to older students.

Finally, average test scores may decline due to worsened achievement among children whose parents lose jobs. Our results are highly consistent with such a mechanism, as race groups are much more responsive to within-ethnicity job losses. However, as with previous research (Oreopoulos, Page, and Stevens 2008, Stevens and Schaller 2009), our finding is driven by the relationship between student test scores and likely parental job loss within low-education families; there is little evidence of such transmission among high-education families. This does not appear to be simply because low-education families are more likely to experience job loss; even firm closings that are predicted to impact mostly high-education workers do not have harmful effects on children in high-education families. Rather, the results are most consistent with high-education families being better able than low-education families to buffer—financially and/or psychologically—their children against the impacts of parental job loss.

If we assume, however, that the aggregate relationship between job losses and test scores is driven entirely by a change in outcomes for children who experience parental unemployment, with zero impact on the test scores of other children, then the 2.4% of a standard deviation fall in test scores that we measure must reflect a 2.4 standard deviation fall in test scores among the one percent of children whose families lose employment. Such an effect is substantially larger than that measured in studies of parental job loss (Oreopoulos, Page, and Stevens 2008, Stevens and Schaller 2009). It is possible that our effect is larger because of the population under study or the measures used. However, it is also plausible that our estimates reflect negative effects on workers and families who maintain employment but are impacted by their friends' and neighbors' loss of employment and the resulting changes to their communities. Aggregate changes in family stress and psychological resources, which we are unable to measure, may thus help explain the effects of community economic downturns on youth school success. More work is needed in order to understand the ways in which large local job losses may impact children whose parents do not lose their jobs but who are exposed to the resulting downturn in other ways.

Conclusion

The evidence we find is most strongly in favor of a model of family-level impact of losses. However, not all children are equally affected by losses likely to have occurred to their families—our evidence is most consistent with the possibility that children of low-education parents are more vulnerable to the effects of job losses than are children of high-education parents. This finding implies the potential for a stronger role for government in remedying harm to disadvantaged children from local economic shocks, in order to circumvent what is otherwise

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likely to be an educational inequality-increasing result of job destruction. In addition, new measures of community-wide stress and potential interventions to moderate it are an important and promising area for future study.

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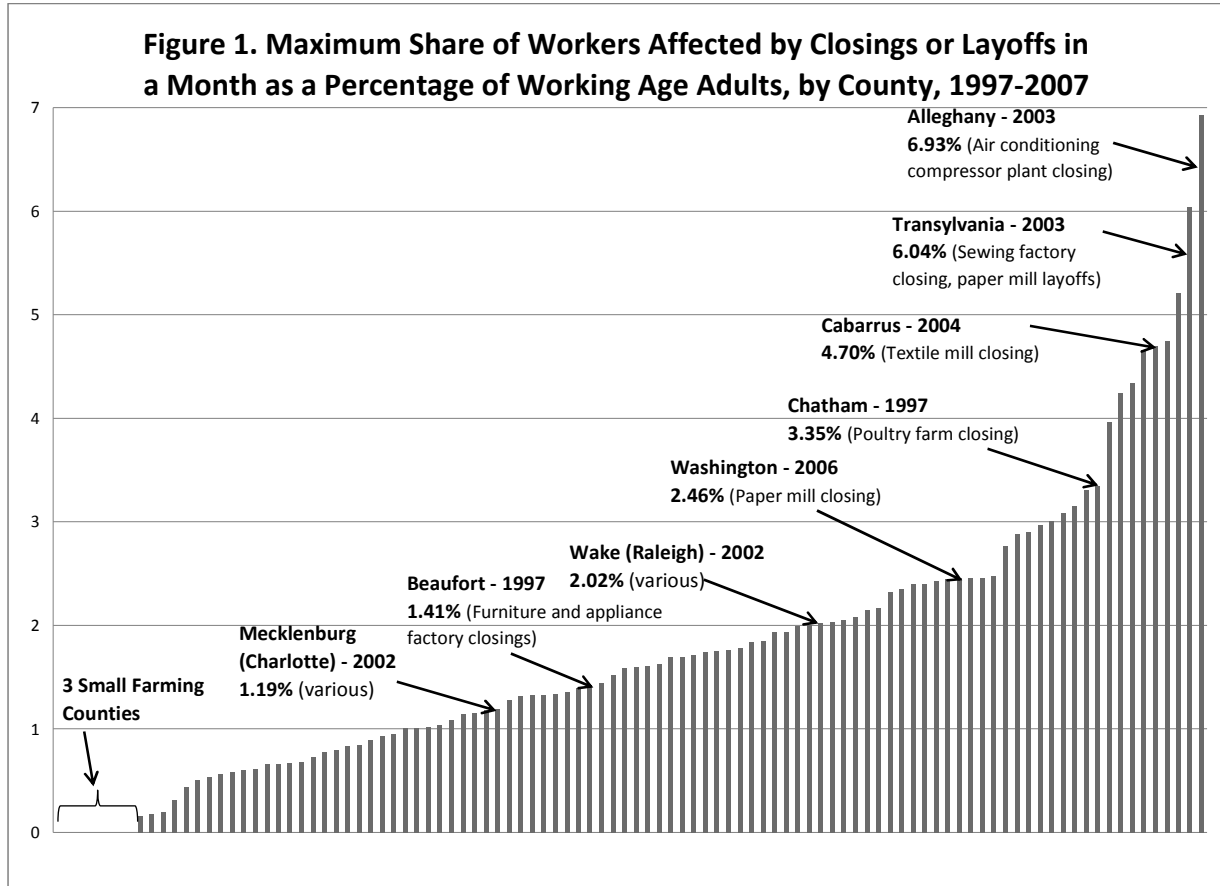
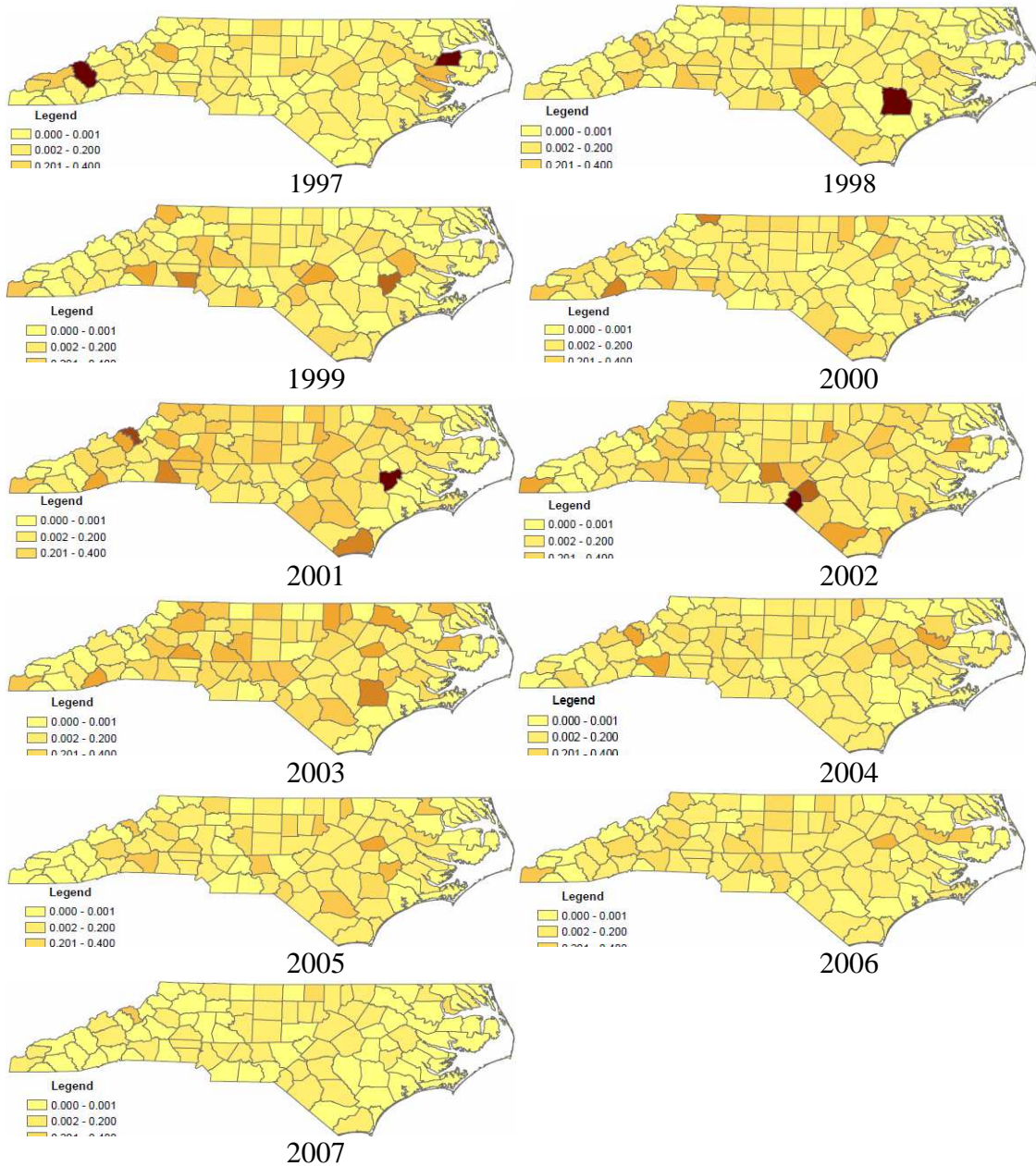


Figure 2. Recency-weighted job losses by county by year.



Shading from 0 to .001 recency-weight percent affected (lightest) to 1.8 to 2+ recency-weight percent affected (darkest) in 0.2 percent increments.

Figure 3.

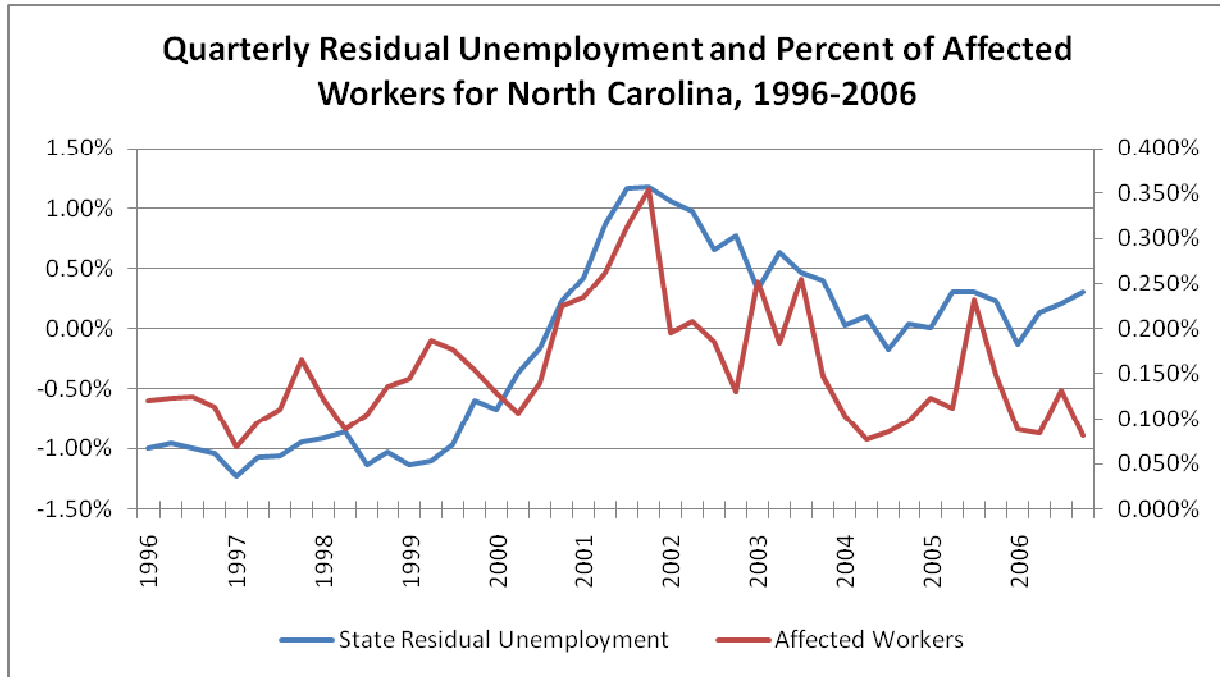


Table 1. Student Demographics

	<u>Percent of total</u>
<u>Ethnicity</u>	
American Indian	1.38
Asian	1.81
Hispanic	4.21
Black	29.13
White	62.16
Multi-Racial/Other	1.31
<u>Gender</u>	
Female	49.63
Male	50.37
<u>Parents' Education (SES proxy)</u>	
Neither parent has more than a HS degree	56.46
At least one parent has some higher education	43.54

N=1,062,522.

Table 2. Test Score Summary Statistics

	<u>Mean</u>	<u>St. Dev.</u>	<u>Min</u>	<u>Max</u>
<u>Reading</u>				
Overall	263.48	9.57	231	290
Low-SES subgroup	259.99	8.89	231	290
High-SES subgroup	268.00	8.45	231	290
<u>Math</u>				
Overall	270.81	11.21	235	310
Low-SES subgroup	266.83	9.81	235	310
High-SES subgroup	276.02	10.78	235	310

N=1,062,522.

Table 3. County Variables

	<u>Mean</u>	<u>Std. Dev</u>	<u>Min</u>	<u>Max</u>
<u>Demographics</u>				
Working Age Population	50908	71552	2158	587183
Unemployment	5.73	2.62	0.80	34.10
Percent Poverty	15.20	4.37	6.80	3.20
Percent Minority	26.52	17.44	0.46	70.19
Percent Black	21.74	16.59	0	62.72
Percent Hispanic	2.96	2.88	0.12	21.14
Percent Asian	0.64	0.78	0	5.70
Percent Other	1.82	5.00	0	39.00
<u>School district characteristics</u>				
Total Per Pupil Expenditures (\$)	7000	1364	4378	15300
One-Year Teacher Turnover (%)	19.81	5.31	5.73	45.16
Tax Revenue per capita	1479	574	0	6300
Dissimilarity Index	0.242	0.173	0	0.820
<u>Test scores</u>				
Average reading score	263.1	2.46	254.7	270.31
Average math score	270.4	3.23	259.6	281.17
<u>Variable of interest</u>				
Affected Percent (Recency Wt.)	0.14	0.26	0	3.32

N=1100 (100 counties X 11 years).

Table 4. Regressions on Math and Reading Scores

<u>Sample universe</u>	<u>Job loss universe</u>	<u>Outcome</u>	
		<u>Reading</u>	<u>Math</u>
All	All	-.014 (.011)	-.015 (.013)
By parents' education:			
HS or less	All	-.024* (.011)	-.024* (.012)
	HS or less	-.042* (.018)	-.036+ (.021)
More than HS	All	-.003 (.014)	-.011 (.020)
	More than HS	-.003 (.029)	-.029 (.045)
By gender and parents' education:			
Girls, HS or less ^a	All	-.024** (.009)	-.024 (.015)
	Women	-.054* (.022)	-.059 (.037)
	Men	-.044** (.015)	-.036 (.025)
Boys, HS or less	All	-.024 (.020)	-.025 (.017)
	Women	-.043 (.044)	-.055 (.035)
	Men	-.044 (.035)	-.039 (.029)
By race/ethnicity and parents' education:			
Whites, HS or less	All	-.018 (.011)	-.018 (.021)
	Whites	-.024+ (.016)	-.026 (.031)
Blacks, HS or less	All	.011 (.023)	-.059+ (.035)
	Blacks	-.033 (.140)	-.338 (.212)
Hispanics, HS or less	All	-.134 (.097)	-.052 (.072)
	Hispanics	-1.251+ (.686)	-.671 (.499)

+p<.10, *p<.05, **p<.01

Robust standard errors in parentheses.

Table 5. Specification Tests					
	Reading		Math		
	<u>b</u>	<u>SE</u>	<u>b</u>	<u>SE</u>	
Robustness checks:					
Quarterly job loss					
losses _q	-.021*	(.009)	-.020*	(.009)	
losses _{q-1}	-0.015+	(.008)	-.019	(.014)	
losses _{q-2}	.008	(.008)	.003	(.008)	
losses _{q-3}	.003	(.007)	.016	(.013)	
Losses in student's original county of residence					
	-0.019+	(.011)	-.020	(.011)	
Falsification check: next year's job losses					
	-.0008	(.004)	.0004	(.005)	
+p<.10, *p<.05, **p<.01					

Robust standard errors in parentheses; all regressions estimated on low-SES subsample.

Table 6. Regressions on Community Level Mediators

Mediator	Sample universe	Model 1: No lags		Model 2: Lags	
		<u>b</u>	<u>SE</u>	<u>b</u>	<u>SE</u>
County per capita tax revenues	All	-10.2	(27.2)	3.45	(29.6)
	Disadvantaged	-82.1*	(41.0)	58.2	(50.4)
Per-pupil expenditures	All	35.4+	(21.0)	20.0	(22.6)
	Disadvantaged	83.4**	(28.5)	79.2*	(29.5)
Teacher turnover	All	.008	(.016)	-.020*	(.008)
	Disadvantaged	.036	(.026)	-.030***	(.008)
Enrollment	All	8.46	(11.84)	-7.50	(10.47)
	Disadvantaged	8.66	(17.58)	-10.1	(14.08)
District segregation	All	.001	(.013)	-.007	(.012)
	Disadvantaged	-.025*	(.010)	-.0003	(.010)
Percent minority	All	-.0004+	(.00021)	-.0003	(.00025)
	Disadvantaged	-.0007+	(.00033)	-.0010**	(.00036)

+p<.10, *p<.05, **p<.01,***p<.001

Disadvantaged sample consists of counties in which more than two-thirds of students' parents have a high school degree or less. Robust standard errors in parentheses.