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CHILDREN LEFT BEHIND:
THE EFFECTS OF STATEWIDE JOB LOSS ON STUDENT ACHIEVEMENT

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ABSTRACT

We examine effects of state-level job losses on student achievement. Losses to 1% of the working-age population decrease eighth-grade math scores by .076 standard deviations, with consistently negative but less precise effects on eighth-grade reading and on fourth-grade math and reading. Effects are 34 times larger than found when comparing students with displaced parents to otherwise similar students, suggesting that downturns affect all students, not just those whose parents lose employment. Evidence is inconsistent with a "downward spiral of behavior" or reduced school funding as causal mechanisms; rather, reduced income and increased distress likely inhibit performance. States experiencing displacement of 1% of workers likely see an 8% increase in schools missing No Child Left Behind requirements.

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Introduction

Increased emphasis on student test scores in recent years has come during a time of significant economic turmoil. Since the No Child Left Behind Act (NCLB) was passed in 2001, the United States has experienced two recessions, including the largest recession since the Great Depression, as well as high rates of job displacement as traditionally U.S.-based industries have moved overseas. Given evidence on the effects of both parental job loss and local-area job loss on youth academic success (Ananat, Gassman-Pines et al. 2011; Stevens and Schaller 2011), it is important to understand how economic downturns may affect aggregate student test scores. Such an understanding is vital to clarifying what affects student test performance and, therefore, to forming both appropriate school accountability policies and approaches to dealing with the community impacts of job destruction.

Studies that attempt to examine the effects of economic losses on academic achievement face two major challenges to validity. First, in most instances, there are likely to be unmeasured or unobserved characteristics that affect both a given family's financial status and the family's well-being. For example, in families facing health or substance-use problems, parents may be less likely to maintain employment and children may also have less school success than in other families. While an instrumental variables approach can be used to address the endogeneity of parental job loss, such an identification strategy still faces a second challenge to validity. That is, it may miss effects of local economic crises on children that come through channels other than parental unemployment. Such channels could include, for example, increased stress among even continuously-employed parents and teachers, or spillover effects in the classroom from peers whose parents lose jobs. Using children whose parents have not lost employment as a control group for those whose parents are displaced, thereby assuming that these other channels are negligible, may understate the effects of job loss on both groups of children. In fact, we find in this paper that research addressing the first but not the second challenge understates the aggregate achievement effects of economic downturns by as much as an order of magnitude.

In this paper, we address these two empirical challenges by examining the impact of state-level job losses caused by business closings and layoffs on states' student achievement test scores. Using plausibly exogenous variation in business closings permits us to identify the causal effect of an economic downturn on all students and on vulnerable subgroups of students in particular. We find that job losses to 1% of a state's working-age population decrease that state's eighth-grade math scores the next year by .076 standard deviations, a large effect size commensurate with (although opposite in sign of) interventions that are *designed* to impact test scores. The results are highly robust to alternative specifications, perform as expected in falsification checks, and are stable across demographic subgroups and the test score distribution.

We investigate potential mechanisms for this decline, and find that it cannot be accounted for by decreased school budgets or by migration. We also present evidence against the drop in test scores representing the outcome of a "downward spiral" of youth behavior after local job losses, such as that depicted in William Julius Wilson's classic book *When Work Disappears* (1996), in which he argues that local job losses lead from idleness among adults to increased antisocial role-modeling behavior, such as drug abuse and violence, and from there to youth antisocial behavior, disengagement from and failure in school. If anything, like adults (Ruhm 2000), students appear to have stable or improved behaviors in the wake of downturns, including reduced use of drugs and alcohol, stable rates of violence, and safer sex practices. By contrast, our results are consistent with the hypothesis that worsened mental health during downturns interferes with students' attainment, and that lowered income can account for some but not all of the decline in scores.

Our findings can provide insight to researchers investigating the determinants of student achievement and to educators seeking to understand the effects of the recent economic crisis. Further, our results have implications for accountability schemes: in a back-of-the-envelope calculation, we find that states experiencing one-year job losses to 1% of their workers likely see an 8% increase in the share of their schools failing to make Adequate Yearly Progress under No Child Left Behind. These results suggest that local economic conditions are an important factor in students' test performance, and so are a relevant consideration for policymakers attempting to fairly and accurately evaluate school performance.

Background

A broad consensus now exists that business layoffs and closings can be viewed as exogenous shocks to workers and communities when conditioning on prior characteristics (Jacobson, LaLonde et al. 1993; Stevens 1997; Sullivan and von Wachter 2009) and that effects on workers and communities subsequent to layoffs and closings can therefore be interpreted as causal effects of job loss. The explanation behind this consensus is as follows. When an individual is fired or quits, it may reflect negative unobservable characteristics of that individual, or of the individual's community. In contrast, however, closings and downsizings occur because of larger macroeconomic and international trade forces. Although firms might close or relocate due to declining worker productivity in an area (which, again, might reflect unobservable community characteristics), empirically it has been repeatedly found that once fixed effects for the area are included, firm decisions are not predictable using changes in community characteristics. In this paper we provide further evidence of this empirical regularity.

One strand of literature has used this empirical strategy to examine the effects of an individual-level job loss (whether a household head loses a job because of a closing, regardless of how many others in the community are affected) on family-level outcomes such as income, parenting practices, or children's grade retention. Another strand has concentrated on the effects of community-level job losses (the total number of jobs lost in a community) on community-wide outcomes such as levels of physical health, suicide, or welfare receipt. However, few papers in this latter strand have looked at children's outcomes. We complement previous work in these two literatures by using a community-level empirical strategy while focusing on children's achievement as the outcome of interest. This approach allows us both to identify causal effects of area job loss and to identify effects on children that do not come solely through their parents' employment status. Below, we discuss the previous individual-level and community-level literatures on the effects of job loss and use them to generate hypotheses on why community-wide job losses might affect aggregate levels of child academic performance.

Effects of individual-level job loss

Parental job loss can affect child development in two ways. First, parental job loss can reduce families' material resources. Second, parental job loss can lead to changes in families' physical health, mental health, and behaviors, including parenting behaviors.

Job loss lowers earnings both in the short term, while parents look for new employment, and over the longer term, because people who lose their jobs due to industry downturns often must start over in new firms and new industries (Jacobson, LaLonde et al. 1993; Stevens 1997).

Family income affects children’s outcomes. Studies have documented that changes in parental income and material resources lead to changes in children’s well-being and, in particular, their achievement test scores (Morris and Gennetian 2003; Dahl and Lochner 2012).

Job loss can also affect children’s outcomes by affecting parents’ mental health and thereby altering family functioning. Individuals who have lost employment have worse psychological (McKee-Ryan, Song et al. 2005) and physical (Sullivan and von Wachter 2009) health than those who have not lost employment. Longitudinal studies that observe families before and after a parental job loss have found that job loss leads to decreased family functioning and impaired parent-child interactions (Jones 1988; Conger and Elder 1994; McLoyd, Jayaratne et al. 1994; Kalil and Wightman 2010). Parental mental health problems and impaired parent-child interactions have both been strongly linked to worse child adjustment and lower levels of school achievement (Elder, Eccles et al. 1995; McLoyd 1998). While it is possible that job loss could lead parents to spend more time with their children, which could have beneficial effects on child school achievement, research has in fact shown that, compared to employed parents, unemployed parents do not spend more time with their children, either in general (Edwards 2008; Kalil and Ziol-Guest 2011) or specifically on education-related activities that could lead to greater academic achievement (Levine 2011).

Researchers have also documented that parental job loss harms children’s school-related outcomes. Longitudinal studies using child fixed effects have shown that parental job loss increases grade repetition (Kalil and DeLeire 2002; Stevens and Schaller 2011) decreases GPAs (Rege, Telle et al. 2011), and increases school-related behavior problems (Hill, Morris et al. 2011). Finally, parental job loss also appears to have long-lasting effects on children into adulthood, such as lower earnings, greater receipt of public assistance, and lower college attendance (Oreopoulos, Page et al. 2008; Coelli 2010).

Effects of community-level job losses

In addition to evidence that job loss worsens outcomes for job losers and their children, there is also evidence that firm layoffs and shutdowns affect those who live in the impacted community, whether they lose employment or not. Several researchers 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; 2005*a*; 2005*b*) examining booms and busts in the steel and coal industries in the 1970s and 1980s found that industry downturns lowered employment not only within but also outside of the initially affected sector. Additionally, those who remain employed in an area that has experienced large job losses also experience decreased earnings (Blanchflower and Oswald 1994). Further, new entrants into the labor market during a downturn experience a lifelong decrease in earnings (Oreopoulos, von Wachter et al. 2012).

In addition to reduced employment and earnings, those who live in an area that has experienced job losses may also experience increased stress and decreased well-being, even when they do not personally experience job loss. Longitudinal research with individual fixed effects has shown that increases in the regional unemployment rate decrease employed individuals' reported life satisfaction (Clark, Knabe et al. 2010; Luechinger, Meier et al. 2010). Similarly, longitudinal cross-national studies have shown that increases in countries' unemployment rates are also associated with decreases in their employed citizens' life satisfaction (Ochsen and Welsch 2006; Ochsen 2008; Clark, Knabe et al. 2010; Luechinger, Meier et al. 2010). Time-series analyses have shown that increases in the local unemployment rate are associated with increases in psychological distress for those who were employed (Dooley and Catalano 1984; Dooley, Catalano et al. 1988). Using two waves of data, Fenwick and Tausig (1994) also found that increases in the local unemployment rate were associated with increases in individuals' psychological distress.

Taken together, the evidence indicates that deteriorating local economic conditions are associated with deteriorating mental health, for those who lose jobs but also for those who remain employed. Well-being could decrease among those who do not lose employment because of increased feelings of job insecurity and anxiety about economic well-being or because of distress for friends and neighbors who have lost work. These changes in adults' mental health could have implications for their children, as parental mental health has been strongly linked with altered family interactions and, in turn, children's developmental outcomes, including school achievement (Downey and Coyne 1990). This could be place to put the "downward spiral of behavior" set up?

These individual changes resulting from community-level job losses could also have large effects on the school setting and on students' experience in schools. For example, given the findings reviewed above, teachers who remain employed may also experience increases in stress. Higher levels of teacher stress are related to lower levels of student academic achievement, mainly through changes in teacher-student classroom interactions (Wiley 2000). Relatedly, if students are in classrooms with peers whose parents have lost jobs, the interactions among students within the classroom may be altered, potentially affecting all students' levels of achievement. Less positive classroom interactions are related to lower growth in children's academic achievement over time (Hamre and Pianta 2001; Pianta, Belsky et al. 2008). For example, increases in one student's behavior problems can disrupt learning by other students in the same classroom (Figlio 2007), and such increases have been found among students who experience parental job loss (Hill, Morris et al. 2011).

In sum, the evidence consistently indicates that those who maintain their jobs in the wake of local job losses experience lower earnings and worse mental health, effects similar to, although less intense than, those experienced by individuals who lose employment. Evidence also strongly suggests that lower earnings and worse mental health among parents lead to lower academic achievement among children. Moreover, changes within schools in teacher stress and in other students' behavior, which can also negatively affect student achievement, are by definition experienced by both those whose parents do and those whose parents do not lose employment. We hypothesize, therefore, that parents who maintain employment in the wake of local job losses, like parents who lose employment, see their children's academic performance decline, albeit by a smaller amount.

Statewide job losses likely affect test scores both through lower achievement among children whose parents lose jobs and through additional area-level mechanisms that affect all children. We do not, therefore, expect that the relationship between statewide job losses and state average test scores will be simply the relationship between individual-level parental job loss and measures of children's academic achievement identified in earlier papers (Kalil and DeLeire 2002; Rege, Telle et al. 2011), scaled by the size of the total job loss in relation to the size of the community. Rather, we expect that our estimate of the total statewide effect will be larger than such a scaled estimate, for two reasons. First, even in a large downturn, most children do not experience parental job loss. Small effects on the majority of children whose parents do not lose employment may, in aggregate, contribute as much or more to the total relationship between statewide job loss and test scores as does the large effect on the minority of children whose parents lose employment. Second, earlier papers have used children who do not experience parental job loss as a control for those who do. If, instead, children who are unaffected by parental job loss experience academic achievement effects in the same direction as those whose parents are affected by job loss, standard "treatment minus control" effect estimates will tend to understate the true effect of parental job loss on child test scores. Based on the literature reviewed above, we believe that effects of statewide job losses will be in the same direction for children whose parents lose jobs and for children whose parents do not, although the magnitude of the effects likely differs. Thus, we hypothesize that our estimates of aggregate effects of state-level job loss on test scores will be considerably larger than would be implied by extrapolations from previous research. We note that it is unlikely that state-level job losses reflect uniform losses in all communities within a state, and hence unlikely that state-level job losses cause uniform changes in test scores across the state. Nonetheless, the relationship between losses averaged across the state and test score changes averaged across the state is interpretable as the aggregate effect of job losses within communities in that state on test scores in communities in that state.

Data

We use two main data sources, one for test score information and one for job loss information. Student academic performance data are from the National Center for Education Statistics' National Assessment of Educational Progress (NAEP), which has administered standardized tests to a nationally representative sample of students in roughly two year intervals since 1964 (National Center for Education Statistics 2010). We focus our analysis on mathematics and reading assessments administered to fourth and eighth graders from 1996 to 2009, which NAEP reports, when available, as state-level average scores and state-level percentile distribution scores for all fifty states and the District of Columbia.[1] The state-level NAEP assessments are given to a representative sample of public school students in each participating state. Scores are reported for students overall as well as for subgroups of students

[1] NAEP also conducts assessments of twelfth-grade students' academic performance, but those data are only available at the state level beginning in 2009, the last year of our panel.

by gender and race.[2] Math assessments were administered in 1996, 2000, 2003, 2005, 2007 and 2009. Reading assessments were administered in 1998, 2002, 2003, 2005, 2007 and 2009. The tests are always administered in the first quarter of the year, between January and March.

Table 1 presents sample descriptive statistics of demographics of students who took the NAEP assessments. The sample is fairly evenly split between male and female students. White students make up the majority of students on average. The national trend over time shows a growth in the share of Hispanic students from seven percent to between 14 and 16 percent and a decline in the share of white students of about 10 percentage points. This pattern is consistent among both fourth and eighth graders. The national share of black students remains stable at about 15 percent. These demographics are consistent with the demographics of children in the United States.

Mean assessment scores and standard deviations for all students and for subgroups of students separately by grade level and test subject are presented in Table 2. The NAEP assessments are designed to have a possible score range of 0 to 500 for individual students. The first two columns in each subject-year grouping represent the mean and standard deviation of the state average assessment scores. The third column contains the averages across years of the national student-level standard deviation for a given assessment and year, which are of course much larger than those for the state averages. Large differences, in expected directions, also exist between the average assessment scores of different subgroups of students. Girls score slightly higher on reading than do boys; white students score significantly higher than black and Hispanic students in both subjects and both grade levels.

For the purposes of analysis, we standardize each state-level assessment score to have a mean of zero and standard deviation of one (following the convention of using the individual student level, not the state, standard deviation), which allows for comparison of test scores across subjects, grades, and years. The sample is organized in state-year observations, yielding a

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2 For eighth graders, scores are also reported by student-reported parental education. However, the distribution of reported parent education in our sample is skewed towards educational attainment higher than is plausible given national estimates (on average, over 45 percent of students in the sample report that at least one of their parents has a college degree, while in the 2000 Census only 28 percent of households with comparably-aged children reported that at least one parent has a college degree) (calculated from IPUMS 2000 5% sample Ruggles, S., M. Sobek, et al. (2004). Integrated Public Use Microdata Series: Version 3.0. [machine readable database] Minneapolis, MN: Minnesota Population Center [producer and distributor]). Thus we do not report analysis by reported parental education. Results for reported-parent-education subgroups are similar to those reported here (available upon request).

maximum of 306 observations for each grade and subject. Not all states administered examinations in all years, and some states did not report assessment scores for all student subgroups. Table A1 in the data appendix lists which states participated in the NAEP assessments for each year of our sample.

Job loss data are from the Bureau of Labor Statistics' (BLS) Mass Layoff Statistics, which report, for each state when available, the number of workers in a quarter who are affected by mass closings or mass layoffs (defined as 50 or more workers) that last longer than thirty days (BLS does not collect data on layoffs or closings affecting fewer than 50 workers). Data are available from 1995 to 2009. For each year, the BLS reports two measures of workers affected by job loss. The first is the total number of initial claimants (TIC), which reflects the total number of workers who filed unemployment claims after a closing or layoff of 50 or more workers. The second is the total number of separations, which is the number of workers who lost jobs because of a mass closing or mass layoff. A mass closing or mass layoff is defined by BLS as one in which 50 workers from the same firm have filed unemployment insurance claims in a 5-week period.[3] Once BLS classifies that event as a mass closing or mass layoff, it then contacts the firm to gather information about the total number of workers who lost jobs in that event (separations). Separations is our preferred measure since it should capture all workers who experience a mass closing or mass layoff instead of just those workers who then also filed unemployment claims. However, the separations measure is likely to suffer from greater measurement error than TIC because it involves the extra step of contacting companies for further information on events that are identified through initial unemployment claims. As discussed in the Methodology section, we combine these two measures in a two-stage least squares approach in order to reduce measurement error.

Table 3 presents summary statistics for separations and TIC. For the purposes of our analysis, we express both separations and TIC as a percentage of the working-age population (defined as the number of state residents aged 25 – 64, measured for each state in the 2000 Census) over a one year time period. On average, 0.71 percent of the working-age population is affected by separations and 0.66 percent file unemployment claims in a year. The variation in

[3] If a firm has layoffs that occur in multiple sites or divisions within a state, those layoffs are treated as a single, firm-level event if they occur for the same economic reason. If, however, layoffs at different sites occur for different economic reasons, BLS treats those as distinct layoff events, in which case, the layoffs at each site would have to meet the 50 worker threshold to qualify as a mass closing or mass layoff event, and thus to be included in the data.

these two measures is roughly the same. Figure 1 plots yearly separations and TIC. The measures are highly correlated, with the percentage of workers reported by firms to be affected by separations slightly higher than the percentage of workers who file for unemployment claims in every year except 2008 and 2009.

As demonstrated in Figure 2, there is substantial variability in job losses across states and years. Figure 2 presents the minimum and maximum percent of workers in each state affected by job separations over the 15 years of our panel. There is significant variation in job losses within states over time, as demonstrated by the difference between the minimum and maximum percent affected in each state, as well as between states. The maximum percentage of workers affected by job loss ranges from less than one half of one percent in Maryland in 2009 to nearly 3.5 percent affected in Alaska in 2009. While the highest observed job loss did occur during the Great Recession (Alaska in 2009), many states experienced their largest losses in the 2002 recession (Colorado, Illinois), or even in years of relatively strong national economic growth, such as 1996 (Maine).

We focus on job loss rather than the state unemployment rate because the unemployment rate can be biased by changes in job-seeking behavior that are confounded with other changes in a community. For example, bad news can discourage workers from looking for work and actually *decrease* the unemployment rate while at the same time increasing community stress and lowering test scores, which would positively bias the estimated relationship between unemployment and test scores. By contrast, firm-level closings and layoffs can more plausibly be viewed as exogenous “shocks” that are driven by the global economy and do not affect test scores other than through their effects on job loss (we also test the exogeneity of these events).

Methodology

In order to explain the effects of job losses on test scores, we estimate the equation:

$$Score_{st} = \beta JobLoss_{st-1} + \delta_t + \delta_s + \varepsilon \qquad (1)$$

In this specification, $Score_{st}$ represents the mean scaled test score for students in state *s* at time *t*. Separate equations are estimated for each of the four subject-grade combinations, as well as for race and gender subgroup scores. In alternative models, we estimate the equation using scaled percentile scores as dependent variables; these models measure whether the effect of job loss is consistent throughout the test score distribution. $JobLoss_{st-1}$ represents the percent of workers in a state affected by mass layoffs for the year-long period up to and including the quarter the tests were administered (this measure is discussed further below). We also include state fixed effects (δ_s) to account for the possibility that states that have higher job losses on average may also have lower test scores on average, and year fixed effects (δ_t) to account for nation-wide time-varying factors that may affect both job losses and test scores.[4] Observations are weighted by the number of test takers. We report heteroskedasticity-robust standard errors that are clustered at the state level.

To measure job loss, $JobLoss_{st}$, we use a composite of two noisy measures, separations and TIC. Use of either measure on its own is likely to lead to attenuation bias, while a composite based on the correlation between the two can increase the reliability of our estimate of job destruction (Angrist and Pischke 2009). The noise in our measure of TIC comes from the fact that not all workers who lose jobs file for unemployment. The noise in our measure of separations is due to the fact that, when contacted by the government, employers may not accurately report the number of workers affected by a layoff. Each measure is composed partly of a "true" signal of underlying job destruction, *D*, and partly of an error term:

$$Separations_{st} = \gamma D_{st} + \varepsilon$$

$$TIC_{st} = \sigma D_{st} + u$$

Where $corr(\varepsilon,u)<1$

The correlation of the two measures, therefore, is:

$$Corr(Separations_{st}, TIC_{st}) = D_{st} + \upsilon,$$

Where $\upsilon < min(\varepsilon,u)$.

Specifically, we estimate a two-stage least squares specification where, in the first stage, we use TIC to predict separations, and then report the coefficient on $\widehat{Separations}_{st-1}$ in an equation predicting $Score_{st}$. Note that $\widehat{Separations}_{st-1}$ is simply $\gamma\widehat{Corr}\ (Separations_{st}, TIC_{st})$. Using the estimated correlation of the two measures as our measure of job loss provides a more precise estimate of job destruction than does either measure on its own (Angrist and Pischke 2009). Using two-stage least squares rather than simply using the correlation as the right-hand side variable in an OLS regression means that our standard errors are automatically adjusted to take into account that $\widehat{Separations}_{st-1}$ is a statistical artifact rather than a direct measurement.

[4] The shallow panel of state-year observations is not deep enough to support precise estimates when state-specific time trends are included; results do not vary significantly from those reported here, but are unstable. While the inability to include trends may raise the concern that unobserved changes in states drive both job losses and declining scores, our extensive falsification checks provide no support for this possibility.

Results

Main estimates

Table 4 presents the results of estimating the impact of job losses on average test scores. In this table each cell represents the coefficient and standard error on separations derived from estimating equation (1) using two-stage least squares for a given subject-grade-subgroup combination. For example, the first cell in the third column is the coefficient derived from estimating the average impact of separations on all students in the sample who took an eighth grade math assessment. The interpretation of this estimate is that job losses that affect one percent of a state's working-age population decrease that state's average eighth-grade math score by 0.076 student-level standard deviations, or by almost three points on average (the student-level standard deviation for the eighth grade math test is 36.4 points).

All 24 point estimates in Table 4 are negative, but only estimates for eighth grade math are consistently statistically significant. Results in Table 4 suggest two main points. First, math scores are more sensitive to job losses than are reading scores. In both the fourth-grade and eighth-grade samples, the point estimates on math assessments are larger in magnitude than those for reading, and this difference is statistically significant in the eighth grade. Second, eighth grade scores are more sensitive to job losses than are fourth grade scores; point estimates are consistently larger for eighth-grade math than for fourth-grade math. These results are consistent with results from our analysis using county-level job loss and academic performance data from North Carolina (Ananat, Gassman-Pines et al. 2011), which also finds effects of job losses on eighth but not fourth grade test scores. Third, eighth grade math scores decline significantly across all gender and race subgroups. Effects do not vary significantly by race or gender, although point estimates for African-Americans are somewhat larger than for other groups. Effect sizes average -.076 standard deviations and point estimates range from -.064 (for Hispanics) to -.109 (for African Americans).

The lack of responsiveness of reading scores is consistent with the findings of many school-based interventions (Decker, Mayer et al. 2004; Abdulkadiroglu, Angrist et al. 2009; Hoxby and Murarka 2009; Angrist, Dynarski et al. 2010; Dobbie and Fryer in press). It may be that math skills are more highly influenced by factors external to the family, including the school and community contexts, than reading skills, which may be more highly influenced by the family context. It may also be the case that math test scores are more sensitive to recent influences than are reading scores, since it may be easier to isolate and test recently-taught math concepts on an exam than it is to isolate particular reading skills. Further research is needed to understand why math scores may be more responsive than reading scores to changes in the immediate economic circumstances of students' communities.

The lack of responsiveness of fourth grade test scores is also consistent with the developmental literature. Older children who are just entering adolescence are likely more developmentally vulnerable than younger children in the period of middle childhood (Eccles, Midgley et al. 1993). In addition, families are better able to shield younger children from the effects of job losses; research has shown that as youth age, they become more aware of their families' economic pressures (Mistry, Benner et al. 2009). Finally, adolescence is a developmental period marked by the increasing importance of peers (Eccles, Midgley et al. 1993). Because adolescents are more likely to interact with a peer whose parent has lost a job than are younger children, any effects through peer interactions of community-wide job losses will be stronger for adolescents.

Percentile test scores

We have also used two stage least squares to estimate equation (1) while replacing average state scores with percentile scores as the dependent variable. The percentile results for eighth graders are presented in Table 5.[5] As in Table 4, each cell presents the coefficient and standard error on separations from a separate regression for each of the various subgroups and for both math and reading. These results follow the same pattern as the results when using average test scores as an outcome. Math scores are typically more responsive to job losses than are reading scores. Point estimates for black students' test scores across the distribution are more negative than are white or Hispanic students'. Notably, effects are quite uniform across the distribution; it does not appear that the effects on average test scores are driven by a few students "bombing" the test after job losses while other students' scores are stable. Rather, effects on students across the distribution appear to cluster around -.076 standard deviations, ranging from a maximum of -.055 standard deviations for whites at the 90th percentile to a minimum of -.139 standard deviations for blacks at the 50th percentile.

[5] The results for fourth-grade students, similar to those for the average test scores outcome measure, do not exhibit statistical significance and are not presented here (available upon request).

Robustness checks

Our main results – that math scores are more sensitive to job losses than reading scores, and that eighth graders are more sensitive to job losses than fourth graders – are robust across subgroups of students and are also robust to percentile outcome measures. In this section we discuss seven other robustness checks (results are summarized in Table 6; estimates from all of these checks are available upon request).

First, we estimated the model 51 times, excluding each state and the District of Columbia individually. While the state fixed effects we include in our model will absorb any persistent relationship between test scores and job loss in a particular state, these specifications test whether severe events in a particular state (such as Hurricane Katrina in Louisiana) that can cause above-average job losses and below-average test scores significantly affect our results. All results are similar when dropping each state, meaning that no single state is driving our results.

Second, we performed a similar exercise excluding each year. While the year fixed effects we include in our model will absorb the effects of any nationwide phenomenon that affected both job loss and test scores in a given year, these specifications further test whether severe events that may have affected both outcomes in only some parts of the country (such as 9/11 on the mid-Atlantic region) significantly affect our results. All results are similar when dropping each year, meaning that no one-time sub-national event is driving our results.

Third, we ran unweighted regressions. While the analysis on which our main results are based weighs each state-year observation by the number of test takers in that state and year (and, where appropriate, subgroup), this analysis treats all state-year observations equally. Whereas our main results can therefore be interpreted as reporting the effects in the typical state in which a student lives (the results most important to a national policymaker), these results can be interpreted as the effects on a state itself (a result important to state policymakers). Analysis conducted using unweighted observations obtains results that are substantially similar to those shown here.

Fourth, we conducted analysis using only subsets of states for which we were not missing data on racial subgroups. Because of geographical variation in the size of the population of black and Hispanic students, some states did not report subgroup scores for either or both black or Hispanic students in some years. In order to test whether the differential estimated responses to job losses experienced by black students compared to white or Hispanic students was driven by larger proportions of black students living in regions that are more sensitive to job loss, we estimated models using only the subsample of state-years for which there were no missing observations for blacks. The racial differences in point estimates of sensitivity to job losses are robust to this specification change. We performed a similar exercise using observations on Hispanic students and obtained similar results.

Fifth, we conducted analysis using only a balanced panel of states for which we are never missing job losses or NAEP scores in years in which the tests are conducted. (Table A1 lists, for each state, the years in which it reported test scores, job losses, and both.) We did so in order to test whether the estimated responses to job losses are influenced by the inclusion of states that only selectively report job losses or test scores (whose participation decisions in BLS data collection and/or NAEP data collection are perhaps influenced by their economies or by their expected scores). Because we have a shallow panel of only at most six observations for each state-grade-test, this robustness check likely reduces measurement error as well (since state fixed effects are unlikely to be well estimated for states that are observed fewer than six times, meaning that such states will contribute significant noise to our estimates). In fact, while the number of students we observe is reduced by 40% under the restriction that job losses are never missing, the estimated effect of a 1% job loss on eighth-grade math scores increases by 50% to -0.114 standard deviations, and the t-statistic increases as well, to 3.7. Similarly, while the number of students we observe is reduced by 29% under the restriction that NAEP scores are never missing, the estimated effect of a 1% job loss on eighth-grade math scores increases by 26% to -.096 standard deviations, and the t-statistic is stable at 2.8. These results suggest that our estimates are not only robust to but actually strengthened by restricting to a balanced panel.

Sixth, we examined the effects of job loss on test scores using only the subset of state-years in which the state started the year with a high (above the median for the full panel of states) unemployment rate. Given the mechanisms we propose through which we believe job losses affect child academic achievement, we hypothesize that job losses should matter more in times and places when the local economy is already under stress. We believe job losses will have stronger effects on stress, on family and community functioning, and subsequently on test scores, when a high pre-existing unemployment rate makes it more difficult for those who experience job displacement to find a new job. That is in fact what we find: in areas with high current unemployment, the estimated effect of a 1% job loss on eighth-grade math scores increases by 28% to -.097 standard deviations, and precision increases as well.

Finally, we have run models including a variety of important time-varying covariates and results do not change. These include characteristics of state populations, including percent of the state population who are minors (under age 18), percent who are elderly (age 65 or older), percent who are white, black, and Hispanic, education structure of the state (percent of adults 25 and older who are high school dropouts, high school graduates, have some college education, and are college graduates), and percent who are poor. We have also estimated our models controlling for characteristics of the student test-taker population, including percent of students who are white, black, and Hispanic and percent of students who are eligible for free or reduced-priced lunch. Finally, we have controlled for underlying economic conditions in the state, including: the average unemployment rate in the year preceding the test; unemployment insurance claims per capita in the year preceding the test; state GDP; and the home foreclosure rate in the state in the year preceding the test.

Falsification checks

We conducted falsification checks in which we estimated equation (1) using future job losses, i.e. losses in the four quarters following the test, instead of lagged job losses. Significant estimates from these regressions would cast doubt on our identifying assumption that job losses, conditional on state and year fixed effects, can be viewed as exogenous shocks to states. Such results would instead suggest that states that experience above-average job losses in a given year already had declining test scores. However, the results of the falsification checks, which are presented in Table 7, are generally small and statistically insignificant. Only two of the twenty coefficients are marginally significant at the 10% level, and of these one is in the unexpected (positive) direction. One of the twenty results presented is significant at the 5% level, and it, too, is in the unexpected (positive) direction. These estimates lend support to the assumption that changes in state test scores do not occur until after job losses occur, and hence the relationship between job losses and test scores can be interpreted causally.

We also conducted falsification checks in which we estimated equation (1) using state population counts for 13- and 14-year-olds as the outcome (measured in the American Community Survey), in order to examine whether our results were being driven by migration patterns (see Table 8). Significant effects of job losses on migration patterns would affect the interpretation of our results by raising the possibility that some of the effect of job loss on test scores might stem from changes in the composition of students taking the tests. For example, if students with higher test scores were more likely to move out of state in response to job losses, lower test scores may be (at least partially) explained by migration and not changes in student performance. However, outmigration in response to industry downsizing is believed to take an entire generation to complete (Blanchard and Katz 1992), and so it is not surprising that we find no relationship between job losses and the total number of 13- and 14-year-olds in a given state the following year. We also find no evidence of changes in test-taker gender or race composition after job losses.

Examining the state population as a whole, again using data from the American Community Survey (ACS), we see no effect of job losses on the share of the population that is elderly or on racial or educational composition of the state. Again, this is consistent with the short time frame of our analysis combined with the fact that outmigration in response to economic changes is a generational process. We do, however, see a marginally significant effect of job losses on the share of the population that is poor, which is consistent with our expectation that job losses increase economic distress. This finding also provides reassurance that our lack of statistically significant effects for other population characteristics reflects an actual lack of migration and not merely noise and imprecision in the ACS data.

Interpretation

Policymakers and researchers alike have so far paid little attention to the potential effects of job losses on aggregate test scores, although they do frequently acknowledge the struggles of children facing parental job loss. One likely explanation for this oversight is that observers assume that the aggregate impacts of job loss are simply the difference in outcomes between children whose parents do and do not lose jobs (e.g., those found by Kalil and DeLeire 2002; Hill, Morris et al. 2011; Rege, Telle et al. 2011) scaled by the share of workers who lose jobs. Since these studies find that students who face parental job loss experience outcome declines of .06 to .17 standard deviations relative to students who do not face parental job loss, observers who extrapolate from these studies to predict population-level effects of a 1% job loss would estimate effect sizes of .0006 to .0017 standard deviations. Even taking into consideration that, according to analysis of the ACS, 1.5% of eighth-graders experience job loss within the household when there is a job loss to 1% of the working-age population, estimates would still be .0009 to .00255 standard deviations. Based on such calculations, a policymaker would erroneously conclude that aggregate effects of job losses on test scores are negligible.

Our estimate of .076 standard deviations is more than an order of magnitude larger. We believe that this difference is due to the fact that our methodology captures negative effects of job loss on workers and families who maintain employment but are affected by their friends' and neighbors' job loss and the resulting changes to their communities and classrooms. If we assume that these other children are affected by statewide job loss, albeit less severely than those who experience parental unemployment, it becomes straightforward to reconcile our study with the findings of earlier studies that contrast the two groups of children, as illustrated in Table 9.

For example, suppose that the 98.5% of children whose parents do not lose employment, but who are indirectly affected either at home or at school, experience test score declines that are one-third the magnitude of the decline experienced by the 1.5% of students who experience household job loss, a scenario displayed in row 5 of Table 9. In that case, a .222 standard deviation decrease in math scores among students who parents lose jobs would imply a .074 standard deviation decrease among other students, and the combination of these effects would produce a .076 standard deviation decrease in the state. The combination would also produce a .15 standard deviation decrease in the test scores of children experiencing parental job loss *relative* to other children, exactly the estimate that Kalil and DeLeire (2002) report for this difference. Note that extrapolating from the Kalil and DeLeire estimate by assuming that children whose parents do not lose employment experience zero declines, however, would miss 97% of the total impact in this scenario, since impacts one-third the size occur to a group nearly 100 times larger.

Comparing our estimates to those in two other studies that use the same approach as Kalil and DeLeire (2002), by Hill et al.(2011)[6] and Rege et al. (2011), suggests effects on children who do not experience parental job loss that are 30-56% the size of the effects on those who do experience parental job loss (see rows 4 and 8 of Table 9). These magnitudes, while striking, are consistent with the effects of downturns on adults who maintain employment

[6] We use the OLS estimates from Hill et al., as their OLS empirical strategy is most comparable to the strategy that we and the other papers we discuss employ.

relative to those who lose employment; for example, Dooley, Catalano et al. (1988) find that a one-standard-deviation increase in the local unemployment rate increases an individual's psychological distress by one-fourth as much as does personal job loss.

It is not necessary to find large spillovers plausible in order to be struck by the share of aggregate effects missed when focusing only on children who experience parental job loss, however. As can be seen in row 2 of Table 9, even if the indirect impact is only one-tenth the size of the direct impact of job loss, analysis focusing solely on children who experience parental job loss would miss 88% of the aggregate impact of job destruction. Readers who are skeptical of the mere existence of any effects on children who do not experience household job loss should note that zero effect of job losses on the test scores of children who are not directly impacted is implausible, as that would require a 5-standard-deviation decline in the average test scores of children who experience parental job loss (row 1 of Table 9).

Mechanisms

Given the evidence for sizeable aggregate declines in test scores, of a magnitude plausible only if driven both by directly and indirectly affected children, it is worth exploring through what mechanisms job losses may drive declines, a task to which we turn next. We consider four possibilities: changes in income; changes in school resources; changes in behavior; and changes in mental health.

Family income. Family income appears to have causal effects on children's academic achievement. Dahl and Lochner (2012) find that an increase in family income of 20 percent increases test scores by .06 standard deviations. This magnitude, however, suggests that average family income would need to fall by more than a quarter in order to cause a .076 standard deviation decline in test scores. A job loss to 1% of a state's working-age population leads, according to an analysis of the ACS, to a decline in the mean income of households containing a 13- or 14-year-old of only about 2% (declines greater than 4% can be ruled out with 95% confidence). Thus, while income losses are almost certainly a partial cause of the decline in test scores, additional mechanisms must be at work.

School resources. Another possible reason for declining test scores after job losses is that, in the face of downturns, school budgets are reduced. We examine this possibility in Table 10, which presents data from the National Center for Education Statistics' National Public

Education Financial Survey. A job loss to 1% of a state's working-age population has small negative but insignificant effects on state and local educational revenues per pupil. It has a significant, but positive, effect on transfers from the federal government, consistent with the fact that federal education support to the states is partially compensatory. However, the effect on federal payments is quite small ($75 per pupil); the fact that it is significant while the effect on state revenues is not, despite being larger at -$147, likely reflects the fact that federal payments are measured with less error.

Likewise, the effects of job losses on instructional expenditures, support expenditures, and total educational expenditures per pupil are negative but insignificant and small. The point estimate for the change in per pupil education expenditures, -$190, represents less than 1.5% of per pupil spending. There is little evidence that changes in school spending of this magnitude have measureable effects on student achievement (Hanushek 2003), and it is highly unlikely that they can account for the large and significant effects on test scores that we find.

<u>Behavior</u>. In his classic book *When Work Disappears* (1996), William Julius Wilson argues that local job losses lead from idleness among adults to increased antisocial role-modeling behavior, such as drug abuse and violence, and from there to youth antisocial behavior, disengagement from and failure in school. We examine the possibility of such a "downward spiral of behavior" using data on teen behaviors taken from the Youth Risk Behavior Survey (YRBS). The YRBS is fielded biannually in February through April of odd years by the Centers for Disease Control (CDC), and is the definitive source of widely-reported statistics such as the share of teens who are sexually active or who have experimented with illegal drugs.

Table 11 presents results from regressions estimating the effect of a job loss to 1% of the working-age population on youth behaviors. Students are significantly less likely to report having consumed alcohol and insignificantly less likely to have used marijuana after job losses. They report significantly fewer recent (over the last 3 months) sex partners and are significantly more likely to have used contraception the last time they had sex. There is no change in the probability of having carried a weapon to school in the past year, or in having engaged in a physical fight. These results are not consistent with a "downward spiral of behavior"; rather, like adults (Ruhm 2000), youth appear to have better behaviors during downturns. We find no evidence that antisocial behavior trends can account for the decline in test scores.

Mental health problems. The last column of Table 11 shows the effects of job losses on the probability that a youth has made plans to commit suicide over the past year, a behavior also tracked in the YRBS. There is a significant rise in this activity of about 8 percent, from a base of 1 in 10 teens. This suggests emotional distress among youth during downturns on par with increases in adult distress. Moreover, it suggests that, as among adults (Fenwick and Tausig 1994), distress is widespread rather than concentrated among those who experience household job loss; in order for directly impacted youth to drive these findings entirely, half of them would have to have made plans for suicide in the past year, an implausible magnitude. Because mental health problems can inhibit learning (Fergusson and Woodward 2002), and because a near doubling in a right-tail outcome such as suicide planning is suggestive of other changes across the distribution of mental health problems, we believe this mechanism may account for a considerable part of the decline in test scores we observe.

Conclusion

This paper finds that students experience sizeable declines in eighth-grade math test scores in the wake of economic downturns. We argue that students who do not experience parental job loss, as well as those who do, are hurt by downturns. The failure in previous research to capture effects on the former group of students means that inferences drawn from that research have understated aggregate effects of downturns by an order of magnitude. When correctly measured, aggregate effects are comparable to effects of policy interventions, such as Tennessee STAR (Word 1990), that have generated enormous policy interest. States with large job losses (we observe maximum losses of 3.4%) are predicted to experience average test score declines of over 25% of a standard deviation, or nearly 10 points. The magnitude of these effects suggests that costs to students from downturns are a relevant consideration, along with other costs of recessions, for policymakers considering economic stimulus and other policies to mitigate effects of the business cycle.

In addition, in this era of greatly increased focus on school accountability for student performance, education policy makers and leaders should be cognizant of the external factors that can negatively influence student achievement. Given the accountability standards enacted in NCLB legislation, even small changes in average test scores could have large implications, if they change schools' proficiency levels. In the 2009-10 school year, 38% of schools failed to make Adequate Yearly Progress (AYP) as mandated under NCLB (Center on Education Policy 2011). Under conservative assumptions, we estimate that a state that experienced a downturn leading to job losses to 1% of its workers (a magnitude that we observe in most states during our panel) would have had only 35% of its schools fail to achieve AYP in the absence of a downturn, an 8% decline.[7]

Statewide job losses, which result from factors external to schools such as pressure from globalization and macroeconomic conditions, can significantly influence student achievement and are well beyond the control of teachers and school administrators. The significant effect these losses can have on schools' abilities to meet accountability goals suggests that policymakers may want to consider recent economic change when defining whether a school is meeting accountability targets.

[7] This calculation assumes: that school-level test score standard deviations are closer to student than to state standard deviations (30 points, compared to 36 for students and 9 for states, a conservative assumption); and that school averages are normally distributed.

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Table 1. Descriptive Statistics - Student Demographics by Year and Subject

Year	1996	1998	2000	2002	2003	2005	2007	2009
Subject	Math	Reading	Math	Reading	Both	Both	Both	Both
A. fourth Grade								
% Male	51	49	50	51	51	51	51	51
Race/Ethnicity								
% Black	16	17	18	19	17	16	15	15
% Hispanic	7	7	9	10	12	15	16	16
% White	71	67	65	64	64	61	61	61
B. eighth Grade								
% Male	50	49	50	50	51	51	50	51
Race/Ethnicity								
% Black	15	16	16	17	15	15	15	15
% Hispanic	7	8	7	9	10	13	14	14
% White	72	67	69	67	68	64	63	63

Source: National Center for Education Statistics - http://nces.ed.gov/nationsreportcard/

Table 2. Descriptive Statistics - Test Scores by Grade Level, Subject and Subgroup

	Math			Reading		
	Mean[1]	St.Dev.[2]	Indiv. Std. Dev.[3]	Mean	St.Dev.	Indiv. Std. Dev.
A. fourth Grade						
All Students	234	9.4	29.1	218	7.7	36.4
Gender						
Female	233	9.2	28.3	221	7.5	35.7
Male	235	9.7	29.8	214	8.1	36.8
Race/Ethnicity						
Black	214	10.7	26.8	198	8.0	34.4
Hispanic	223	9.3	27.6	202	8.1	36.3
White	241	8.1	25.9	227	5.1	32.7
B. eighth Grade						
All Students	277	9.6	36.4	262	6.8	34.8
Gender						
Female	276	9.4	35.3	267	6.7	33.7
Male	278	9.8	37.5	257	7.0	35.2
Race/Ethnicity						
Black	252	9.9	33.3	243	5.2	33.1
Hispanic	261	8.6	34.2	246	5.8	35.1
White	286	7.5	32.7	270	4.3	31.5

1. *Mean* is computed by taking the average across states and years of the reported state-level averages of individual student scores. The mean is weighted at the state level by the number of students in each state.
2. *St. Dev.* Is computed by taking the standard deviation across states and years of the reported state-level averages of individual student scores, and weighted at the state level by the number of student in each state.
3. *Indiv. Std. Dev.* Is computed by taking an average across years of the national student-level standard deviations reported by NAEP for a given assessment and year

Source: National Center for Education Statistics - http://nces.ed.gov/nationsreportcard/

Table 3. Descriptive Statistics - Job Losses as a Percent of Working Age Population

	Obs.	Mean	Std. Dev.	Min	Max
Separations[1]	506	0.71	0.47	0	3.39
Total Initial Claimants[2]	506	0.66	0.47	0	3.66

1. Separations is calculated by dividing the total yearly number of separations in a state by the working age population (ages 25-64) in that state.
2. Total Initial Claimants is calculated by dividing the total yearly number of claimants in a state by the working age population (ages 25-64) in that state.

Source: Bureau of Labor Statistics - http://www.bls.gov/mls/

Table 4. Estimation Results - Impact of Job Losses on Student Test Scores

	Fourth Grade	Eighth Grade

	Math	Reading	Math	Reading
All Students	-0.032	-0.013	-0.076***	-0.009
	(0.035)	(0.020)	(0.027)	(0.022)
Student Subgroups				
Gender				
Female	-0.033	-0.003	-0.077***	-0.007
	(0.029)	(0.018)	(0.029)	(0.019)
Male	-0.023	-0.022	-0.072***	-0.022
	(0.038)	(0.024)	(0.027)	(0.025)
Race/Ethnicity				
Black	-0.010	-0.015	-0.109**	-0.042
	(0.042)	(0.035)	(0.049)	(0.041)
Hispanic	-0.014	-0.011	-0.064***	-0.028
	(0.051)	(0.023)	(0.024)	(0.017)
White	-0.049	-0.029	-0.066*	-0.002
	(0.037)	(0.022)	(0.036)	(0.026)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each cell represents the coefficient and standard error on *Separations* derived from estimating equation (2) for a given subject-grade-subgroup combination. The specification equation (2) includes both state and year fixed effects.

Source: Bureau of Labor Statistics; National Center for Education Statistics

Table 5. Estimation Results - Impact of Job Losses on Percentile Test Score Outcomes (8th Grade)

	Math					Reading				
Percentile	**10th**	**25th**	**50th**	**75th**	**90th**	**10th**	**25th**	**50th**	**75th**	**90th**
All Students	-0.078**	-0.081**	-0.077***	-0.071***	-0.064***	-0.048	-0.023	-0.008	0.001	0.009
	(0.039)	(0.033)	(0.026)	(0.024)	(0.023)	(0.034)	(0.029)	(0.021)	(0.015)	(0.015)
Student Subgroups										
Gender										
Female	-0.087**	-0.087***	-0.076***	-0.069**	-0.071***	-0.034	-0.013	0.003	0.009	0.020
	(0.036)	(0.033)	(0.028)	(0.027)	(0.026)	(0.033)	(0.025)	(0.017)	(0.017)	(0.019)
Male	-0.069	-0.075**	-0.077***	-0.077***	-0.055***	-0.061	-0.028	-0.017	-0.009	-0.004
	(0.043)	(0.033)	(0.027)	(0.023)	(0.021)	(0.042)	(0.035)	(0.026)	(0.020)	(0.017)
Race/Ethnicity										
Black	-0.101	-0.122**	-0.139***	-0.118***	-0.089*	0.005	-0.030	-0.042	-0.051	-0.055
	(0.066)	(0.051)	(0.043)	(0.043)	(0.046)	(0.054)	(0.039)	(0.038)	(0.044)	(0.042)
Hispanic	-0.058	-0.065**	-0.059***	-0.077***	-0.056*	-0.076***	-0.033	-0.005	-0.006	0.022
	(0.041)	(0.027)	(0.022)	(0.024)	(0.029)	(0.028)	(0.026)	(0.028)	(0.021)	(0.025)
White	-0.059	-0.065	-0.068**	-0.062**	-0.055*	-0.026	-0.008	0.001	0.006	0.018
	(0.051)	(0.043)	(0.034)	(0.031)	(0.029)	(0.051)	(0.035)	(0.023)	(0.019)	(0.016)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each cell represents the coefficient and standard error on *Separations* derived from estimating equation (2) for a given subject-grade-subgroup combination. The specification in equation (2) includes state and year fixed effects.

Table 6. Robustness checks: Effect of job losses on eighth grade math scores when:

Restricting sample to:		Controlling for:						
balanced panel of states	state-years with above median unemployment rate	state demographics (age, race, and education structure)	test-taker demographics (race and free lunch status)	state unemployment rate	state UI claims per capita	state GDP	foreclosures	unweighted
-0.123***	-0.097**	-0.075***	-0.075***	-0.061***	-0.063***	-0.073***	-0.060***	-0.076**
(0.031)	(0.029)	(0.027)	(0.026)	(0.024)	(0.024)	(0.027)	(0.022)	(0.030)

Table 7. Falsification Results - Impact of Future Job Losses on Student Test Scores

	4th Grade			8th Grade	
	Math	Reading		Math	Reading
All Students	-0.003	0.02		-0.016	0.001
	-(0.026)	-(0.017)		-(0.024)	-(0.013)
Student Subgroups					
Gender					
Female	-0.013	0.018		-0.007	0.018
	-(0.025)	-(0.014)		-(0.021)	-(0.016)
Male	0.006	0.024		-0.032	-0.007
	-(0.027)	-(0.028)		-(0.024)	-(0.012)
Race/Ethnicity					
Black	0.045*	0.049*		0.01	-0.001
	-(0.019)	-(0.022)		-(0.022)	-(0.030)
Hispanic	-0.117	-0.037		-0.094**	-0.014
	(0.000)	-(0.023)		-(0.028)	-(0.035)
White	-0.023	0.011		-0.014	0.002
	-(0.024)	-(0.013)		-(0.027)	-(0.014)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each cell represents the coefficient and standard error on *Separations* derived from estimating the specification for a given subject-grade-subgroup combination. The specification includes state and year fixed effects.

Table 8. Falsification results: Effects of 1% job loss on:

Percent of state population that is:									State population of 13- and 14-year-olds	Percent of testtakers who are:				Per-pupil expenditures
elderly	black	white	Hispanic	high school dropouts	high school graduates	has some college	college graduates	poor		male	white	black	Hispanic	
0.079	-0.08	0.111	-0.204	0.048	-0.032	0.028	-0.043	0.897+		0.256	-0.021	-0.411	-0.000	-81.926
(0.062)	(0.095)	(0.251)	(0.156)	(0.158)	(0.137)	(0.099)	(0.115)	(0.492)		(0.318)	(1.243)	(0.436)	(0.947)	(353.798)

Table 9. Calibration: Combinations of direct and indirect effects consistent with a population average effect of .076 SD from a 1% job loss

	A	B	C	D	E	F	G
	Spillover	Direct effect (SD) on 1.5% of population who experience parental job loss	Indirect effect on 98.5% of population who do not experience parental job loss	Difference between those who do and do not experience parental job loss	Papers finding the difference listed in column D	Estimated population effect (SD) when extrapolating to aggregate effect from column D (i.e. when assuming spillover = 0)	Share of true effect missed when extrapolating to aggregate effect from column D (i.e. when assuming spillover = 0)
(1)	0.00	5.067	0.000	5.067		0.076	0.0%
(2)	0.10	0.670	0.067	0.603		0.009	88.1%
(3)	0.20	0.358	0.072	0.287		0.004	94.3%
(4)	0.30	0.245	0.073	0.171	Hill et al.	0.003	96.6%
(5)	0.33	0.222	0.074	0.148	Kalil and DeLeire	0.002	97.1%
(6)	0.40	0.186	0.074	0.111		0.002	97.8%
(7)	0.50	0.150	0.075	0.075		0.001	98.5%
(8)	0.56	0.135	0.075	0.060	Rege et al.	0.001	98.8%
(9)	0.80	0.095	0.076	0.019		0.000	99.6%
(10)	1.00	0.076	0.076	0.000		0.000	100.0%

"Spillover" refers to effects on children whose parents do not experience job loss as a percentage of the *true* direct effect on children whose parents experience job loss.

Table 10. Estimated Results - Impact of Job Losses on Per Pupil School Finance

	State Revenues	Local Revenues	Federal Revenues	Instructional Expenditure	Support Expenditure	Total Ed Expenditure
	-147.798	25.181	75.315**	-124.612	-24.218	-190.217
	(165.129)	(92.002)	(30.035)	(123.329)	(59.629)	(213.867)
Mean	6,739.691***	5,404.253***	883.414***	7,272.405***	4,136.522***	13,110.528***
	(277.550)	(186.979)	(63.403)	(215.322)	(114.867)	(363.359)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11. Youth behaviors

	Ever used alcohol	Ever used marijuana	Ever had sex	Number of recent sex partners	Used contraception last time had sex	Carried a weapon to school in the last year	Physical fight in the last year	Felt unsafe at school in the last year	Suicidal thoughts in the last year	Suicidal plans in the last year
All Students	-0.0236***	-0.0149	0.0024	-0.0514**	0.1249***	-0.0049	0.0037	0.0059	0.0046	0.0083*
	(0.0081)	(0.0094)	(0.0118)	(0.0245)	(0.0124)	(0.0035)	(0.0074)	(0.0046)	(0.0055)	(0.0048)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each cell represents the coefficient and standard error on *Separations*. The specification includes state and year fixed effects.

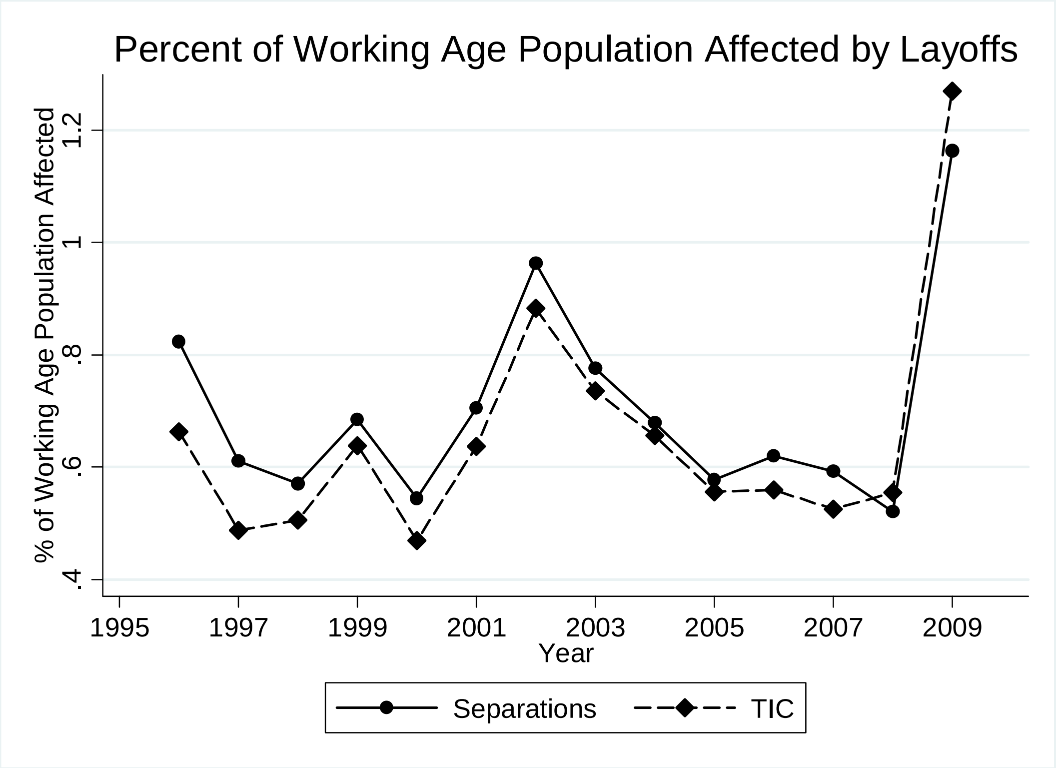

Figure 1. National Percent of Working Age Population Affected by Layoffs as Represented by Separations and Total Initial Unemployment Claims

Source: Bureau of Labor Statistics - http://www.bls.gov/mls/

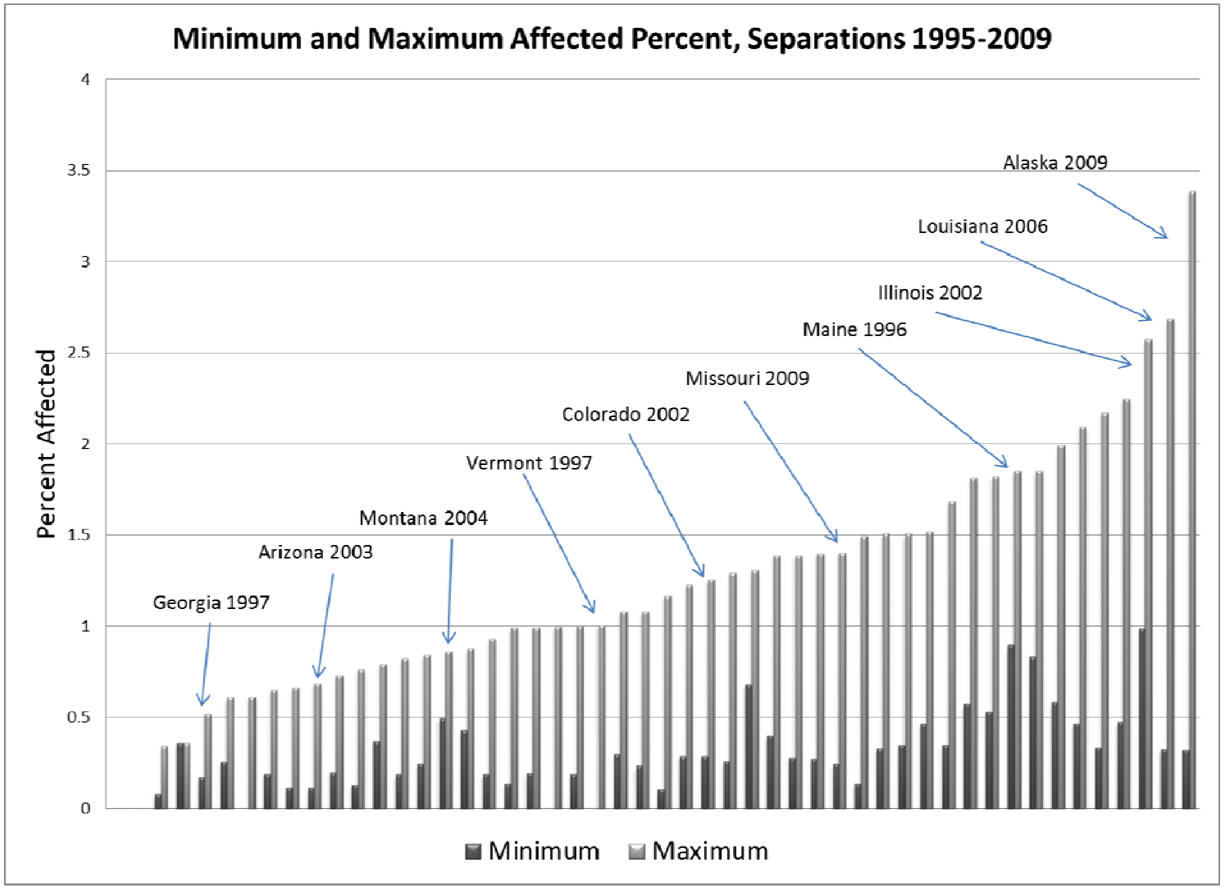

Figure 2. Minimum and Maximum Percent of Working Age Population Affected by Job Loss, 1995-2009

Source: Bureau of Labor Statistics - http://www.bls.gov/mls/

Table A1. States Reporting both Test Score and Job Loss Data

Year	1996	1998	2000	2002	2003	2005	2007	2009
Test Subject	Math	Reading	Math	Reading	Both	Both	Both	Both
Alabama	T, J	T	T,J	T,J	T	T	T,J	T,J
Alaska	T, J			J	T,J	T	T,J	T,J
Arizona	T	T	T,J	T,J	T,J	T,J	T,J	T,J
Arkansas	T, J	T	T,J	T,J	T,J	T	T,J	T,J
California	T, J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Colorado	T, J	T		J	T,J	T	T,J	T,J
Connecticut	T, J	T	T,J	T,J	T,J	T,J	T,J	T,J
Delaware	T	T,J		T,J	T	T	T	T,J
District of Columbia	T	T	T	T	T	T	T	T
Florida	T, J	T,J	J	T,J	T,J	T,J	T,J	T,J
Georgia	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Hawaii	T	T,J	T,J	T,J	T	T	T,J	T,J
Idaho	J	J	T	T,J	T,J	T,J	T,J	T,J
Illinois	J	J	T,J	J	T,J	T,J	T,J	T,J
Indiana	T,J	J	T,J	T,J	T,J	T,J	T,J	T,J
Iowa	T	J	J	J	T,J	T,J	T	T,J
Kansas	J	T	T,J	T,J	T,J	T,J	T,J	T,J
Kentucky	T	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Louisiana	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J

Maine	T,J	T,J	T	T,J	T	T	T	T,J
Maryland	T,J	T,J	T,J	T,J	T,J	T	T,J	T,J
Massachusetts	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Michigan	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Minnesota	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Mississippi	T,J	T,J	T,J	T,J	T,J	T,J	T	T,J
Missouri	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Montana	T,J	T	T	T	T,J	T	T	T,J
Nebraska	T		T	T	T,J	T	T	T
Nevada	J	T,J	T,J	T,J	T	T	T	T,J
New Hampshire				J	T	T	T	T
New Jersey	J	J	J	J	T,J	T,J	T,J	T,J
New Mexico	T	T,J	T	T,J	T	T	T,J	T,J
New York	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
North Carolina	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
North Dakota	T	J	T	T	T,J	T,J	T	T
Ohio	J	J	T,J	T,J	T,J	T,J	T,J	T,J
Oklahoma		T,J	T	T,J	T,J	T	T,J	T,J
Oregon	T	T	T,J	T,J	T,J	T,J	T,J	T,J
Pennsylvania	J	J	J	T,J	T,J	T,J	T,J	T,J
Rhode Island	T	T	T	T,J	T	T	T	T
South Carolina	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
South Dakota			J		T	T	T	T
Tennessee	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Texas	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Utah	T	T	T,J	T,J	T	T	T,J	T

Vermont	T,J	J	T	T	T	T	T	T
Virginia	T,J	T,J	T,J	T,J	T,J	T,J	T,J	T,J
Washington	T,J	T,J	J	T,J	T,J	T,J	T,J	T,J
West Virginia	T,J	T	T	T	T,J	T	T,J	T
Wisconsin	T,J	T,J	J	J	T,J	T,J	T,J	T,J
Wyoming	T	T	T	T	T	T	T	T
# of States Reporting Both	28	25	28	36	38	30	37	41

T – NAEP test score data are available for a given state-year

J – BLS mass closing or mass layoff data are available for a given state-year

Source: Bureau of Labor Statistics - http://www.bls.gov/mls/

National Center for Education Statistics - http://nces.ed.gov/nationsreportcard/