The Effects of Local Job Destruction on Youth Mobility

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I. Introduction

One major threat to intergenerational mobility in the U.S. stems from the fact that, while college-going has increased considerably over the last 40 years among high-income families, it has risen much less among middle- and, especially, low-income families (Bailey & Dynarski, 2011). One factor that can influence children's college enrollment is parental job loss; recent research has found that parental job loss in the year children were 17 significantly decreased the probability that children would enroll in college (Coelli, 2010; Oreopoulos, Page, & Stevens, 2008). Because aggregate employment volatility among low- and middle-wage workers has increased in recent years due to globalization and the transition to a "knowledge economy," these findings raise the question of whether such volatility can help account for the divergence in college-going rates among the children of high- and low-skilled workers.

Initial work by Chetty et al. (2014) examining economic change and intergenerational mobility found some evidence of a relationship between an area's long-run risk of job displacement (through Chinese competition, measured with data provided by (Autor, Dorn, & Hanson, 2013) and intergenerational mobility, but estimates were noisy and imprecise. This paper tests the hypothesis that community-wide job losses that are realized at a critical life stage for a given cohort—adolescence—substantially affect its aggregate mobility, and that by leveraging the timing of job losses relative to this life stage it is possible to identify the effects of macroeconomic change on intergenerational mobility.

The direction of effects of job destruction on inequality in education is ex ante ambiguous. Economic change, particularly skill-biased technical change, incentivizes educational investment. If many of the children of high-income parents are already on track to attend college, then the marginal college-goers due to structural change may be the children of low-income parents; in this case, local job losses will decrease inequality in college attendance. However, because aggregate job losses disproportionately hit the already disadvantaged, and because parental job loss decreases the probability of college attendance, it is also possible that local job losses will increase inequality in college attendance. For parallel reasons, effects of job losses on intergenerational income mobility are similarly ambiguous.

Using aggregate annual job destruction for all 50 states over the period 1995-2012, we investigate the effects of macro-level job loss on inequality in college attendance, as measured by the parent income-child college attendance at age 19 gradient. We further examine the effects on the parent income-child income at age 26 gradient. We find that job losses at ages 12 through 17 significantly increase inequality in college attendance at age 19 and modestly increase intergenerational inequality in income at age 26, particularly in areas that are relatively disadvantaged on a variety of dimensions. In falsification tests, we find no evidence of reverse causality between changes in inequality and job losses, and no evidence that an omitted third factor causes both.

II. Previous literature

Both family job losses and community-wide job losses affect children's success in school. Within families, parental job loss lowers children's test scores, increases grade retention, and lowers college-going (Coelli, 2010; Oreopoulos et al., 2008; Stevens & Schaller, 2011). At the community level, our own work has shown that aggregate community-wide job loss also lowers aggregate test scores (Ananat, Francis, Gassman-Pines, & Gibson-Davis, 2013; Ananat, Gassman-Pines, & Gibson-Davis, 2011). In contrast, however, aggregate college attendance increases when local economic conditions worsen (Betts & McFarland, 1995).

Beyond schooling outcomes, worsening economic conditions also lead to changes in youth well-being in different directions. Prosocial behaviors, like avoiding drugs and alcohol and using contraception, increase during recessions, among both adults and adolescents (Ananat, Francis, et al., 2013; Ananat, Gassman-Pines, & Gibson-Davis, 2013; Ruhm, 2000). At the same time, however, both adults' and adolescents' mental health decreases when economic conditions worsen (Catalano et al., 2011; Gassman-Pines, Ananat, & Gibson-Davis, 2014). Effects on mental health are particularly pronounced for already disadvantaged groups, including African-American youth.

Taken together, this set of results indicates that it is unclear what the net effect of community-wide job losses on college attendance or early adult income will be for any subgroup of the population. Moreover, depending on which effect dominates at each point in the income distribution, job losses could increase or decrease overall inequality in college-going and later income. Given that job losses to individuals, and the attendant decrease in college attendance, tend to be disproportionately concentrated among the low-skilled and racial minorities (Bartik, 1993; Fairlie & Kletzer, 1998; Kletzer, 1998), we hypothesize that area job losses will increase inequality in college attendance. In addition, given that other effects of communities' job losses are larger for African-Americans (Ananat, Gassman-Pines, et al., 2013; Gassman-Pines et al., 2014), we hypothesize that the increase in inequality will be greater in areas with larger black populations. Because the negative effects of local job loss are likely to be greater when new jobs are scarce, we also hypothesize that the increase in inequality will be greater when pre-existing unemployment is high. Further, we hypothesize that redistributive policy at the state level can help ameliorate the effects of job destruction on intergenerational mobility.

III. Data

In this section we describe the data. Unweighted summary statistics for key measures are shown in Table 1. Statistics weighted by states' number of children or total African-American population are substantially similar (results available upon request).

1. Outcome data on intergenerational mobility

Our outcome data come from the Equality of Opportunity Project (Chetty et al. 2014). Data on the parent income-child enrolled in college at age 19 gradient (income-college gradient) by commuting zone is available for cohorts born in 1984-1993. To generate state-level measures of the income-college gradient, we average these outcomes for all the commuting zones within a state, weighted by the population of the commuting zone. As reported in the top panel of Table 1, this gradient averages .71 across states and cohort birth-years, with a standard deviation of .06. We use the identical process to generate state-level measures of the parent income-income at age 26 gradient (parent-child income gradient), which is available by community zone for cohorts born in 1980-1987. For the state-cohort birth-years used in our analyses, the income-income gradient has a mean of .26 and standard deviation .05.

2. Job loss data

The predictor of interest is aggregate community job loss due to layoffs and closings when a cohort is in adolescence, 12 to 17 years of age. This measure of economic downturns, which reflects shocks to local labor demand, offers significant advantages over more conventionally used measures, such as changes in the unemployment rate or employment-to-population ratio, that capture labor supply-side changes as well as labor demand-side changes.

First, it reflects an unanticipated "shock" to a community: research has demonstrated that community job losses typically reflect global changes in technology and trade, rather than being driven by changes in either individual or community characteristics that might also directly affect intergenerational mobility (Ananat, Francis, et al., 2013; Ananat et al., 2011; Ananat, Gassman-Pines, et al., 2013; Jacobson, LaLonde, & Sullivan, 1993).

Additionally, because it isolates demand-side changes, this measure of job loss represents an unambiguously negative piece of economic news. In contrast, although a decline in the unemployment rate is usually labeled as "good news," the unemployment rate could go down because labor supply goes down as the unemployed become discouraged and stop looking for work, which is actually bad news. Indeed, by our own calculations, in 1 out of 3 months, U.S. total jobs and the unemployment rate either both increase or both decrease simultaneously. Similarly, the employment-to-population ratio can go down, usually labeled "bad news," because increased wealth decreases labor supply by allowing more families to have one adult stay home with the children, retire early, or go back to school, all of which are actually good news.

Data on job losses in the 50 U.S. states are from the Bureau of Labor Statistics' (BLS) Mass Layoff Statistics, which provides quarterly observations for each state from 1995 to 2012. For each quarter, 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.[1] 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).

The second panel of Table 1 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 in each state and year, taken from the National Cancer Institute's Surveillance Epidemiology and End Results data) over the period that a cohort is 12 to 17 years of age. On average, 3.6 percent of the working-age population is affected by separations and 3.3 percent file unemployment claims over such a period; a one-standard deviation increase in job loss raises those figures to 5.9 and 5.5 percent, respectively.

As demonstrated in Figure 1, there is substantial variability in job losses across states and years. Figure 1 presents the minimum and maximum percent of workers in each state affected by job separations in a single year over 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 South Dakota to nearly 4.5 percent in Alaska, both in 2009. While many of the highest observed job losses did occur during

[1] 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.

the Great Recession, some states experienced their largest losses in the 2002 recession (Colorado, Illinois), after the Great Recession's official end (Maryland, 2012), or even in years of relatively strong national economic growth, such as 1997 (Maine).

Separations is our preferred measure of job loss, 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.

This combined measure has been well-validated in our previous work. It has been shown to predict changes in student test scores, youth risk behaviors, and mental health (Ananat, Francis, et al., 2013; Ananat, Gassman-Pines, et al., 2013; Gassman-Pines et al., 2014). In addition, falsification tests have demonstrated no link between future job losses and current outcomes on any of these measures, bolstering our confidence that these job losses are not anticipated and can be viewed as quasi-experimental changes to communities.

3. State policy data

We include several measures of the state policy environment, in order to test whether state safety net or human capital investment policies moderate the effects of job losses on intergenerational mobility. In order to avoid the inclusion of endogenous policy responses to job loss in our analysis, we use the policies in place the year each cohort was age 11, prior to the occurrence of the relevant job losses at ages 12 to 17. Summary statistics for these measures are shown in the bottom panel of Table 1.

First, the generosity of states' unemployment insurance (UI) systems comes from the Employment and Training Administration (ETA) in the U.S. Department of Labor. The ETA provides, for each state and year: the replacement rate, or the proportion of workers' wages replaced by UI benefits; and the maximum amount of covered employees' wages upon which benefits are based. We match each cohort with the state UI benefit policies in place the year before the relevant job losses occurred. The average UI replacement rate over this period is 47 percent.

Second, data on public K-12 education funding are from the National Center for Education Statistics (NCES) National Public Education Financial Survey Data. These data provide, for each state and year, per pupil total expenditures by category and per pupil revenues from local, state and federal sources. After converting each figure into 2013 dollars, we match each cohort with the average spending and revenue in its state the year before the relevant job losses occurred. The average per-pupil spending over this period is $10,949.

Third, data on state college tuition policies are from the NCES Integrated Postsecondary Education Data System, which provides annual information on tuition for all postsecondary institutions that participate in federal student aid programs. We utilize these data to examine in-state tuition costs at public universities. We match each cohort with the tuition policy in place the year before the relevant job losses occurred. The average tuition is $6120.

IV. Method

We estimate the following equation:

$$Gradient_{sy} = \beta \sum_{i=12}^{17} JobLoss_{sy+i} + \delta_y + \delta_s + \varepsilon \quad (1)$$

where $Gradient_{sy}$ reflects either the parent-child income gradient or the income-college gradient for the cohort born in year y in state s, and $\mathrm{JobLoss}_{\mathrm{sy+i}}$ reflects the total job loss due to layoffs and closings in state s in the year that cohort is age *i*. The equation includes fixed effects δ_y for cohort, to control for nation-wide events for those born in a given year that may affect mobility, and fixed effects δ_s for state, to control for time-invariant characteristics of a place that may affect mobility across cohorts. Standard errors are clustered at the state level to allow for arbitrary correlation between errors in observations within a state over time.

To measure job loss, $JobLoss_{sy}$, 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 & 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 or closing. Each measure is composed partly of a “true” signal of underlying job destruction, *D*, and partly of an error term:

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

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

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

The correlation of the two measures, therefore, is:

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

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

Specifically, we estimate a two-stage least squares specification where, in the first stage, we use $\sum_{i=12}^{17} TIC_{sy+i}$ to predict $\sum_{i=12}^{17} Separations_{sy+i}$, and then report the coefficient on $\sum_{\iota=12}^{17} \widehat{Separations}_{sy+\iota}$ in an equation predicting $Gradient_{ys}$. Note that $\sum_{\iota=12}^{17} \widehat{Separations}_{sy+\iota}$ is simply $\gamma\widehat{Corr}\ \left(\sum_{i=12}^{17} Separations_{sy+i}, \sum_{i=12}^{17} TIC_{sy+i}\right)$. 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 & 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 $\sum_{\iota=12}^{17} \widehat{Separations}_{sy+\iota}$ is a statistical artifact rather than a direct measurement.

The coefficient of interest, β, captures the effect of job losses to 1% of an area's working-age population in the years a cohort is in adolescence (ages 12-17) on the relationship between parental income and child college attendance at age 19 or parental income and child income at age 26. A positive and significant estimate of β would imply that local economic downturns increase the importance of parental income for youth outcomes and thereby reduce intergenerational mobility. A negative and significant estimate would imply that local downturns "level the playing field" for youth as they transition to adulthood. A precisely-estimated zero value for β would imply that, despite evidence that experiencing parental job loss in adolescence lowers the probability of a successful transition to adulthood, such impacts are not large enough to affect aggregate mobility, and therefore are relatively inconsequential for macro policy around intergenerational mobility (although, of course, possibly important for other areas of policy).

In addition to estimating equation (1) using state-level observations weighted by the number of children in each state, we also estimate it weighting by total African-American population. This allows us, without benefit of access to separate measures of inequality by race, to test whether job losses have stronger effects on inequality in areas with larger black populations. We also estimate equation (1) separately for cohorts experiencing different initial economic conditions, as proxied by the level of unemployment, when they are age 11 and about to enter adolescence. This allows us to validate our results against previous work finding that the effects of job destruction are greater in contexts where new jobs are scarce.

Finally, we estimate equation (1) separately for states with different social safety net policies. We test whether job losses have stronger effects on inequality in college-going in places with lower unemployment benefits, less generous public elementary and secondary school funding, or higher public university tuition.

V. Results

Our main estimates of the effects of job loss on inequality in college attendance at age 19 and in income at age 26 are shown in Table 2. The upper left panel presents estimates for all available cohorts, weighted by cohort size. Point estimates are suggestive of increases in inequality—a one-standard deviation increase in job losses, 2.2 percent, leads to an estimated .16 standard deviation increase in the income-college gradient and a .06 standard deviation increase in the parent-child income gradient—but are not statistically significant at conventional levels.

In the lower left panel, however, which shows the estimates when weighting observations by the size of the black population, the effects are large and statistically significant. In the typical area where an African-American lives, a one-standard deviation increase in job loss leads to a .29 standard deviation increase in inequality in college attendance ($p < .05$) and a .19 standard deviation increase in intergenerational inequality of income at age 26 ($p < .10$).

The right panel presents results only for those cohorts that experienced above-median pre-existing unemployment prior to the relevant job losses, which previous research suggests should exacerbate any effects of job destruction. Indeed, for these cohorts, effects of job loss on inequality in college attendance are large and statistically significant when weighted by either the overall population ($p < .05$) or the African-American population ($p < .01$); a one-standard deviation increase in job loss leads to a .21 or .37 standard deviation increase, respectively, for the two weighting schemes.

However, we cannot find effects on the parent-child income gradient solely for high-unemployment areas. Data constraints for the income gradient as an outcome mean that we can only estimate equation (1) for three cohorts for which we can observe job losses throughout the adolescent period (N=153 state cohort birth-years when including all states and the District of Columbia). Splitting the sample to examine effects of job losses in different environments reduces the sample size still further, and results in too few degrees of freedom (N=77) to estimate equation (1). Hence, we do not examine the income gradient in our context analysis below.

Table 3 presents the effects on the college gradient under different policy environments. The left panel displays results for cohorts experiencing below- and above-median levels of spending on public primary and secondary education when cohorts were age 11. Results indicate that the consequences of job loss on the college gradient vary by K-12 education funding. A one standard deviation increase in job losses in a below-median spending state where a typical African-American resides leads to a .45 standard deviation increase in inequality in college attendance ($p < .001$); effects smaller than .26 standard deviations can be ruled out with 95% confidence. Even in the below-median spending state where the typical American resides, the maximum likelihood estimate of the effect is a .36 standard deviation increase ($p < .01$); effects smaller than .15 standard deviations can be ruled out with 95% confidence. Effects of job loss on the college gradient are much smaller and not statistically significant in states with above-median K-12 education spending.

The middle panel of Table 3 displays results for cohorts experiencing different levels of post-secondary tuition. Overall, the measured effects of job loss on the college gradient are similar between high- and low-tuition states and the overall sample of states, but are less precisely estimated because of the halved sample size for each regression. The lack of meaningful differences between high- and low-tuition areas could suggest that tuition when a cohort is age 11 is too distal a measure to have meaningful effects on youth college-attendance decisions, or because generosity of financial aid has a larger influence on college-going than the sticker price of tuition.

The right panel of Table 3 shows results for cohorts in states with above- and below-median levels of UI replacement rates at age 11. Effects of job loss on the college gradient appear to be concentrated in areas with higher UI replacement rates. We note, however, that UI replacement rates are endogenously high when pre-existing unemployment is high. Thus, these results may best be viewed as an alternative version of the right panel in Table 2 rather than a test of the efficacy of UI spending.

Table 4 presents, as a falsification check, the results of estimating equation (1) but substituting community job losses during ages 12 to 17 with job losses at age 20. If, as found in previous research (Ananat, Francis, et al., 2013; Ananat et al., 2011; Ananat, Gassman-Pines, et al., 2013; Jacobson et al., 1993), job losses are (a) not anticipated by community members and (b) not driven by underlying changes in the community that also affect college-going, then future job losses should have no correlation with current inequality in college attendance. That is indeed what we find: community job losses at age 20 have a statistically insignificant relationship with inequality in college enrollment at age 19, for both the area where the typical child resides and where the typical African American resides. Moreover, job losses at age 20 have no effect on the gradient of parent income and child income at age 26, despite the fact that in this case the outcome does in fact follow the predictor temporally. This null finding is unlikely to be due to small sample size, as for this set of years the parent-child income gradient regressions are estimated with N=357 state-years of birth. This null result suggests that job losses affect intergenerational mobility through processes in the teen years, not through some sort of direct effect on adults from different backgrounds.

VI. Discussion

This paper investigates the effects of macro-level job loss on intergenerational inequality in college attendance, as measured by the gradient of parent income with child college attendance at age 19, and intergenerational inequality in income, as measured by the gradient of parent income with child income at age 26. We focus on cumulative job losses during a key developmental period, adolescence, and find that job losses during that period significantly increase intergenerational inequality in college attendance at age 19 and modestly increase intergenerational inequality in income at age 26, particularly in areas that are relatively disadvantaged on any of a variety of dimensions. Importantly, in falsification tests, we find no evidence of reverse causality between changes in inequality and job losses, and no evidence that an omitted third factor causes both.

The effects of job loss on intergenerational inequality in college attendance are very large for cohorts for which any of our measures of state-level disadvantage hold true. We measure state-level disadvantage in a number of ways, including large African-American population, high pre-existing unemployment, and low K-12 education spending. In each case, when cohorts in states with higher levels of disadvantage experience more job losses during adolescence, there is a stronger association between parents' income and children's college attendance, indicating a larger increase in inequality under such circumstances. Taken together, these results suggest that community job losses exacerbate intergenerational inequality in areas that are also facing other challenges.

Our results are consistent with the hypothesis that effects of job losses on inequality are greater in areas with larger black populations. This hypothesis is derived from our earlier work showing larger effects of community job losses on the test scores, risk-taking behavior and mental health of black adolescents (Ananat, Gassman-Pines, et al., 2013; Gassman-Pines et al., 2014). In the present study, our findings could also indicate that effects are greater on African-Americans. We cannot directly address that, however, as we do not have separate measures of intergenerational mobility for different racial groups. An alternate explanation for our findings could be that policies or social norms in places with larger African-American populations lead job losses to cause increased inequality for all groups, relative to policies and norms extant in places with fewer African-Americans.

We also measure state disadvantage with K-12 education funding and find that job losses have a stronger effect on inequality in college attendance when education funding is low. The fact that job losses have less of an effect on college-going in states with more generous K-12 education funding suggests that education funding may be an important way to "level the playing field," so that experiences outside of school are less consequential for success in later life. Recent research strongly links school spending with positive academic and behavioral outcomes for children (Jackson, Johnson, & Persico, 2014). When states promote such positive outcomes, disadvantaged children in those states may be less likely to be thrown off track by the negative consequences of local job loss.

Contrary to our expectations, we find that the effects of job loss on inequality in college attendance do not vary by the generosity of states' college tuition. Lack of significance by college tuition could be because it is measured too distally (when cohorts are age 11, well before they are deciding to go to college), or because generosity of financial aid matters more for students' college attendance decisions than the sticker price of tuition. However, combined with the importance of K-12 education funding, these results also suggest that human capital and college readiness are at least as important as liquidity constraints in determining effects of job destruction on intergenerational mobility. The fact that job losses at age 20 do not impact the income gradient at age 26 also supports the interpretation that job destruction worsens inequality by harming development in adolescence rather than by mechanically influencing parent-child transfers in adulthood.

We focus primarily on effects on intergenerational inequality in college attendance rather than inequality in income because only three cohorts with income data can be observed during adolescence, making it impossible to split the sample by differences in state policies. Nonetheless, for the full sample, particularly when weighted by the size of the African-American population, results are suggestive that positive effects of job destruction on the college gradient translate into smaller but still positive changes in the income gradient a few years later. Because this suggestive evidence indicates that community job losses strengthen the link between parents' income and children's income at age 26, results are consistent with the possibility that intergenerational mobility in income, as in education, decreases following job losses in adolescence.

In sum, our paper shows that statewide job losses during a critical developmental period, adolescence, lead to decreases in intergenerational mobility, especially in areas that are already disadvantaged. The pattern of finding is particularly strong for mobility as measured by inequality in college attendance. Our results also suggest, however, that it may be possible to ameliorate these negative effects of job destruction on intergenerational mobility through generous funding of public education.

References

Ananat, E. O., Francis, D. V., Gassman-Pines, A., & Gibson-Davis, C. M. (2013). Children left behind: The effects of statewide job loss on student achievement. *NBER Working Paper No. 17104*.

Ananat, E. O., Gassman-Pines, A., & Gibson-Davis, C. M. (2011). The effects of local employment losses on children's educational achievement. In G. J. Duncan & R. Murnane (Eds.), *Whither Opportunity? Rising Inequality and the Uncertain Life Chances of Low-Income Children* (pp. 299-313). New York: Russell Sage Foundation.

Ananat, E. O., Gassman-Pines, A., & Gibson-Davis, C. M. (2013). The Effect of Local Job Loss on Teenage Birthrates: Evidence from North Carolina. *Demography, 50*, 2151-2171.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics*. Princeton, NJ: Princeton University Press.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *The American Economic Review, 103*, 2121-2168.

Bailey, M. J., & Dynarski, S. M. (2011). Gains and gaps: Changing inequality in US college entry and completion. *National Bureau of Economic Research Working Paper No. w17633*.

Bartik, T. J. (1993). Who benefits from local job growth: migrants or the original residents? *Regional Studies, 27*, 297-311.

Betts, J. R., & McFarland, L. L. (1995). Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollments. *The Journal of Human Resources, 30*, 741-765.

Catalano, R. F., Goldman-Mellor, S., Saxton, K., Margerison-Zilko, C., Subbaraman, M., LeWinn, K., & Anderson, E. (2011). The health effects of economic decline. *Annual Review of Public Health, 32*, 431-450.

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States. *National Bureau of Economic Research Working Paper No. w19843*.

Coelli, M. B. (2010). Parental job loss and the education enrollment of youth. *Labour Economics, 18*, 25-35.

Fairlie, R. W., & Kletzer, L. G. (1998). Jobs lost, jobs regained: An analysis of black/white differences in job displacement in the 1980s. *Industrial Relations: A Journal of Economy and Society, 37,* 460-477.

Gassman-Pines, A., Ananat, E. O., & Gibson-Davis, C. M. (2014). Effects of statewide job losses on adolescent suicide-related behaviors. *American Journal of Public Health, 104*, 1964-1970.

Jackson, C. K., Johnson, R., & Persico, C. (2014). The effect of school finance reforms on the distribution of spending, academic achievement, and adult outcomes. *National Bureau of Economic Research Working Paper No. w20118*.

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings Losses of Displaced Workers. *The American Economic Review, 83*, 685-709.

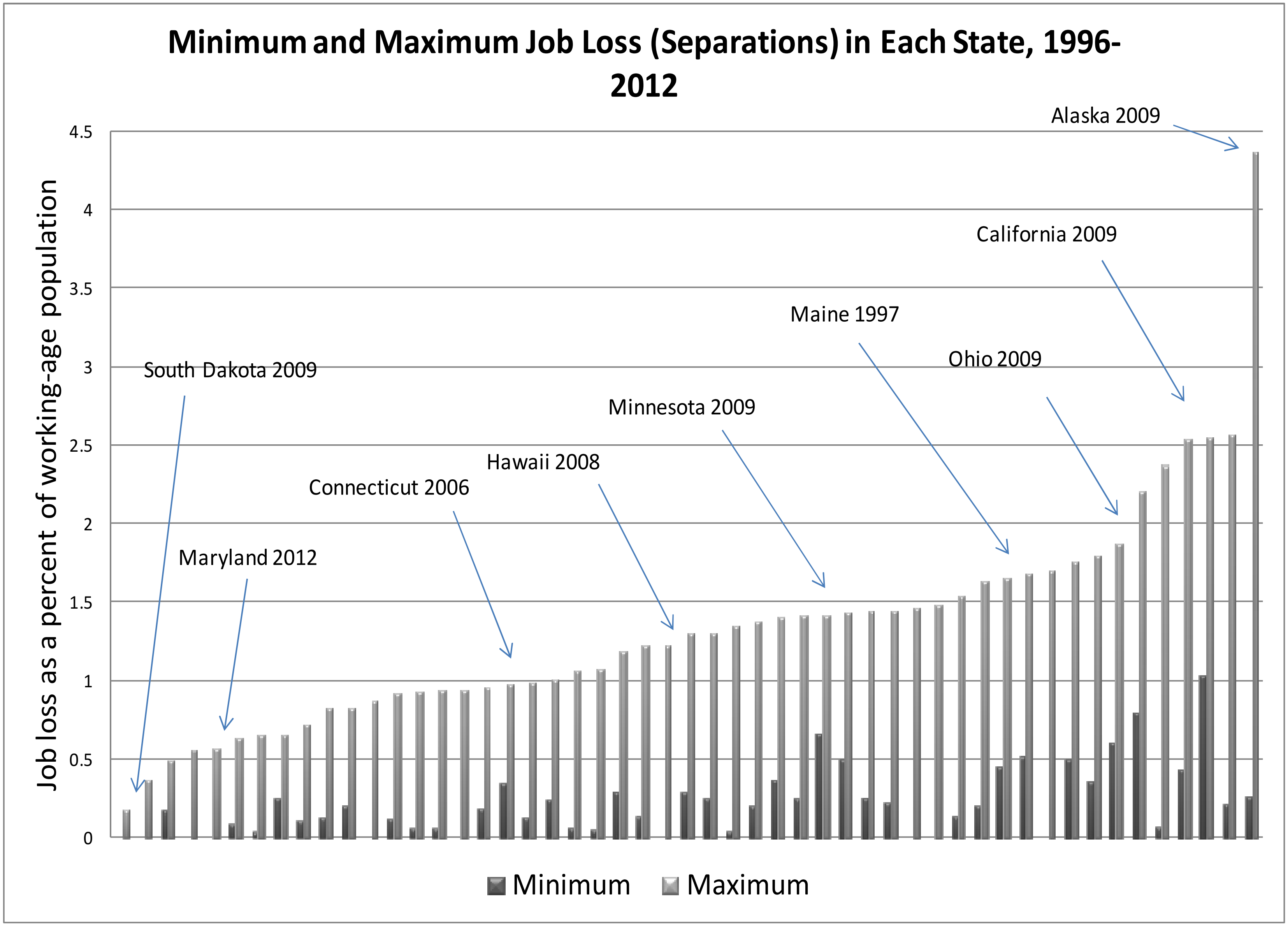
Kletzer, L. G. (1998). Job displacement. *The Journal of Economic Perspectives*, 115-136.

Oreopoulos, P., Page, M. E., & Stevens, A. H. (2008). The intergenerational effects of worker displacement. *Journal of Labor Economics, 24,* 729-760.

Ruhm, C. J. (2000). Are Recessions Good for Your Health? *Quarterly Journal of Economics, 115*, 617-650. doi: 10.1162/003355300554872

Stevens, A. H., & Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Economics of Education Review, 30*, 289-299.

Figure 1



Minimum and Maximum Job Loss (Separations) in Each State, 1996-2012
Job loss as a percent of working-age population
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Alaska 2009
California 2009
Maine 1997
Ohio 2009
South Dakota 2009
Minnesota 2009
Hawaii 2008
Connecticut 2006
Maryland 2012
Minimum
Maximum

Table 1. Summary Statistics

	Mean (SD)
State Intergenerational Mobility Measures	
Gradient of parent income-college at age 19	0.71
	(0.06)
Gradient of parent income-income at age 26	0.26
	(0.05)
State Job Loss over age 12-17	
Separations as a percent of working-age population	3.62
	(2.25)
Total initial claims as a percent of working-age population	3.32
	(2.17)
State Policy Environment at age 11	
Unemployment rate (%)	5.68
	(1.99)
UI replacement rate (%)	47.08
	(5.22)
In-state tuition ($2013)	6,120.42
	(3,075.25)
K-12 spending ($2013)	10,949.18
	(2,843.92)

Note: Averages reported for all 50 states and the District of Columbia for cohorts age 17 in 2001-2010 (N=510), except for income at age 26 gradient, reported for cohorts age 17 in 1997-2003 (N=357). Statistics are similar when weighted by total number of children or African-Americans in the state (results available upon request).

Table 2. Main Results: Total Job Losses at Ages 12-17 Predicting Intergenerational Mobility

	Full Sample				Cohorts experiencing above-median unemployment rate at age 11			
	college at 19		income at 26		college at 19		income at 26	
Weighted by:								
# children	0.0045		0.0013		0.0058	**	-0.0040	
	(0.0032)		(0.0024)		(0.0027)		(0.0074)	
# African-American	0.0078	**	0.0044	*	0.0100	***	-0.0003	
	(0.0025)		(0.0023)		(0.0026)		(0.0069)	
State-years of birth included	*N* = 510		*N* = 153		*N* = 257		*N* = 77	

* $p < .10$. ** $p < .05$. *** $p < .01$.

Note. All models control for state and year fixed effects; heteroskedasticity-robust standard errors are clustered by state.

Table 3. Moderation of Main Effects on College at 19 by Policy Environment

	K-12 spending at age 11				State college tuition at age 11				Unemployment Insurance replacement rate at age 11			
	Below median		Above median		Below median		Above median		Below median		Above median	
Weighted by:												
# children	0.0098	***	0.0029		0.0037		0.0032		-0.0002		0.0123	***
	(0.0029)		(0.0033)		(0.0051)		(0.0039)		(0.0026)		(0.0021)	
# African-American	0.0123	***	0.0060		0.0083		0.0085		0.0041		0.0135	***
	(0.0026)		(0.0038)		(0.0054)		(0.0057)		(0.0026)		(0.0026)	
State-years of birth included	*N* = 255		*N* = 255		*N* = 255		*N* = 255		*N* = 254		*N* = 256	

* $p < .10$. ** $p < .05$. *** $p < .01$.

Note. All models control for state and year fixed effects; heteroskedasticity-robust standard errors are clustered by state.

Table 4. Falsification check: Job Losses at Age 20 Predicting Intergenerational Mobility

	college at 19	income at 26
Weighted by:		
# children	-0.0068	-0.0017
	(0.0044)	(0.0038)
# African-American	-0.0039	0.0001
	(0.0045)	(0.0036)
State-years of birth included	*N* = 459	*N* = 357

* *p* < .10. ** *p* < .05. *** *p* < .01.

Note. All models control for state and year fixed effects; heteroskedasticity-robust standard errors are clustered by state.