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The Intergenerational Consequences of Unexpected Job Loss

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Abstract: This paper uses variation induced by mass layoffs and firm closings to explore the intergenerational effects of family income shocks. Previous studies have argued that mass layoffs and firm closings can be thought of as exogenous employment shocks. Using a Canadian panel of administrative data that follows over 100,000 father-child pairs from 1978 to 1999, and includes detailed information about the firms at which the father worked, we construct narrow treatment and control groups whose fathers had the same level of permanent income prior to 1982 when some of the fathers were displaced. We demonstrate that job loss leads to permanent reductions in family income and compare outcomes among individuals whose fathers experienced an employment shock to outcomes among individuals whose fathers did not. We find that children whose fathers were displaced have annual earnings that are about 10% lower than similar children whose fathers did not experience an employment shock. They are also more likely to receive unemployment insurance and social assistance. The estimates are driven by the experiences of children whose family income was at the bottom of the income distribution, and are robust to a number of specification checks.

It is well known that children from affluent families tend to have higher incomes as adults than children who grow up in poor families (Solon, 1992; Zimmerman, 1992). This pattern has convinced many social scientists and policymakers that family income plays an important role in determining children's life chances. Greg Duncan and Jeanne Brooks-Gunn (1997), for example, suggest that raising the incomes of poor families "…will enhance the cognitive development of children and may improve their chances of success in the labor market during adulthood." Policy discussions often invoke the legacy of growing up in a poor family as evidence of the potential effectiveness of income transfer programs such as Aid to Families with Dependent Children. Yet, the process that generates the intergenerational income correlation is not well understood: one possibility is that it reflects differences in parents' ability to make monetary investments in their children, but another is that it reflects differences in innate characteristics that parents pass onto their children.

Certainly, the magnitude of the intergenerational correlation is hard to ignore. Solon's (1999) survey of the intergenerational mobility literature suggests that the correlation between fathers' and sons' earnings is about 0.4. At issue is the extent to which this correlation reflects the importance of monetary vs. non-monetary family background characteristics. High income parents are likely to have other attributes such as high ability or motivation that independently have a positive affect on their children's outcomes. Cross-sectional comparisons of individuals who grew up in families with different income levels are thus likely to overstate the degree to which family resources matter.

This paper identifies the effect of mass layoffs and firm closings on the next generation's outcomes. Jacobsen, Lalonde and Sullivan (1993) (henceforth, JLS) and Stevens (1997) have documented that workers displaced by such events experience substantive long-lasting reductions in earnings, and they argue that mass layoffs and firm closings can be thought of as exogenous employment shocks. Our estimation strategy constructs narrow "treatment" and "control" groups of individuals whose fathers had the same levels of permanent income prior to 1982 when some of the fathers were displaced. We demonstrate that displacement leads to permanent reductions in family income and compare outcomes among individuals whose fathers experienced an employment shock to outcomes among individuals whose fathers did not.

We find that children whose fathers were displaced have annual earnings that are about 10% lower than similar children whose fathers did not experience an employment shock, even after accounting for fathers' pre-displacement earnings, initial region of work, industry and firm size. They are also more likely to receive unemployment insurance and social assistance. These estimates are driven almost exclusively by the experiences of individuals whose family income during childhood was in the bottom quartile of the income distribution. We estimate smaller effects on individuals who were older than 16 at the time of the father's displacement, and no effects at all on individuals who were older than 19. The results suggest that the long term consequences of unexpected job loss extend beyond the effect on one's own income to the eventual labor market outcomes of one's children.

I. Background

Understanding which factors contribute to the intergenerational transmission of income is crucial to the development of successful public policies. In the United States there are a number of programs designed to help low-income children, including Temporary Assistance to Needy Families, Medicaid, Head Start, Food Stamps, and public education. Some of these involve income transfers whereas others are direct-intervention programs. Mayer (1997) notes that throughout the history of the United States social policy has swung back and forth between the belief that material deprivation is the primary reason that poor children have poor outcomes, and the belief that parental characteristics that contribute to low incomes are mostly responsible for poor children's failure. Informed social policy depends critically on understanding which of these beliefs is correct. If, for example, money is a key determinant of children's outcomes then the effects of policies on family income should be a central consideration when evaluating their costs and benefits. On the other hand, if children's outcomes are mostly determined by innate parental characteristics that are correlated with income then social policy should be less concerned with income redistribution and focus more on addressing deficits in the other characteristics.

A number of cross-sectional studies show that positive income correlations remain even after controlling for a variety of parental characteristics (e.g. Corcoran et. al, 1992; Duncan and Hill, 1987), but these correlations are likely to overstate the degree to which parental income matters if some parental attributes that are positively correlated with income and children's outcomes cannot be observed. It is difficult to find compelling variation in income that is unrelated to parental characteristics that might affect child development (Duncan and Brooks-Gunn, 1997; Haveman and Wolfe, 1995). Shea (2000), for example, uses cross-sectional variation in fathers' earnings due to union status, industry wage differentials and involuntary job loss to identify the effects of parental income, but other researchers (cite) have argued that wage differences associated with these job characteristics reflect workers' innate attributes. Dahl and Lochner (2004) also create an instrument for income that includes family background characteristics (as well as changes in income induced by the Earned Income Tax Credit).[1] Mayer (1997) controls for unobserved parental characteristics by adding to her regression a measure of parental income taken *after* the child's outcome is observed. She argues that future income is exogenous with respect to a previously measured outcome, so that it can serve as a proxy for the unmeasured components of family background. The success of this strategy requires that parental investment when the child is still at home is not influenced by the anticipation of future income, however. Blau (1999), Duncan, et. al. (1998) and Levy and Duncan (1999) all compare outcomes across siblings with different age-specific family income levels, but this approach can only

[1] Dahl and Lochner do not show what happens to their results when family background characteristics are dropped from the instrument. Changes in EITC benefits during the 1990's may generate a useful instrument for family income, but part of the EITC effect is likely driven by changes in labor force participation (e.g. Eissa and Liebman, 1996; Eussa and Hoynes, 2004) which may have an independent effect on children's outcomes.

identify the effect of transitory changes in family income and it has been well documented that permanent income has a much stronger relationship with children's long-term outcomes (Solon, 1999).[2]

Given that many of the usual instruments for parental income are likely to be positively correlated with other parental attributes, it is surprising that much of the research to date has found no evidence that an exogenous increase in family resources would result in improved outcomes. For example, the expected correlation between Shea's instruments and omitted parental characteristics should bias his estimates upward, but his insignificant point estimates frequently imply that money makes children worse off. These findings raise questions about whether resource allocation decisions within families operate to unravel the intended effects of many government transfer programs.

Another explanation for this pattern is that most existing studies have been based on longitudinal datasets such as the Panel Study of Income Dynamics and the National Longitudinal Study of Youth, which are relatively small. It has turned out to be difficult to precisely identify parental income effects with so little data. The confidence interval around Shea's typical estimate of the effect of father's income on children's wages, for example, includes effects ranging from -50% to +30%. Solon's (1999) comparison of sibling and intergenerational earnings correlations suggests that no more than 40% of the similarity in brothers' outcomes is likely due to factors related to their parents' income. While this leaves open the possibility that family income plays an important role in children's development it also suggests that when the data are limited to only a few thousand observations the effect may not be strong enough to estimate precisely.

[2] A very different approach is taken by Acemoglu and Pischke (2001) who use long-run trends in earnings levels at different points in the U.S. earnings distribution (and in different geographic regions) to generate exogenous income variation. They find that demographic groups with more sharply rising incomes also experienced larger increases in their children's educational attainment. One puzzle with these results is that, in their preferred specification, the return to education has no significant effect on college enrollment decisions. This may reflect the fact that their framework makes it difficult to control for both the current return to education and the change in parental income, since both are driven by the same national trends in returns to skill. The rise in return to skill should affect children's education directly, and so their strategy may not provide a valid instrument for changes in parental income.

This paper makes several contributions to the growing literature on intergenerational income mobility. First, by exploiting variation that is induced by mass-layoffs and firm closings, we can separate the effect of a long-lasting income shock from the effect of innate parental attributes. While cross-sectional differences in fathers' labor market characteristics are likely to reflect individual attributes, our longitudinal data allow us to construct narrow groups of "treatment" and "control" children whose families look identical before 1982, when some of the fathers lost their jobs. We base our analysis on a sample of children whose fathers worked continuously for the same firm between 1978 and 1981, and control for average family income, regional location, industry, and firm size during those four years. Thus, we are able to compare outcomes across children whose families would likely have had the same level of permanent income if the treatment fathers had not been displaced. A second advantage of our study is that it makes use of a longitudinal dataset that contains earnings and income observations on over 100,000 father-son pairs. The sheer magnitude of this dataset substantially increases the precision with which intergenerational relationships can be estimated.

II. Empirical Strategy

We conduct our analysis in two stages. In the first stage, we use methods developed in the displacement literature to demonstrate that displacement has a substantive and long-lasting effect on a family's resources. The purpose of this part of the analysis is to make a convincing case that displacement produces an exogenous shock to family income. In the second stage, we use this information to identify the intergenerational effect of a family income shock.

II.A. Estimating the Effect of Displacement on a Family's Resources

We begin by following the empirical strategy introduced by JLS, and demonstrate that displacement has a large, persistent effect on a family's monetary resources. We start by regressing annual measures of family income, father's income and father's earnings on a full set of father's age fixed effects and a set of province by year dummy variables.[3] The residual from this regression provides an annual estimate of family resources that is purged of life-cycle effects, province specific business-cycle effects and province-specific trends in earnings. We then regress this residual on a set of dummy variables indicating whether the father left his firm due to a mass layoff or firm closing in a current, future or previous year. Specifically, given longitudinal data on fathers' labor market experiences, the effect of displacement on a family's resources is modeled in the following way:

$$\ln I_{ipt} = D_{ipt}\delta + \alpha_i + u_{ipt} \qquad (1)$$

where ln I_{ipt} is the log of the residual of family *i*'s resources in province *p* and year *t*, and D_{ipt} is a vector of dummy variables indicating that a displacement has taken (or will take) place in a future, current, or previous year. The error term has two components, a child-specific fixed effect, α_i, and a random component, u_{ipt}. Since the model includes fixed effects, individual characteristics that do not vary over time, such as race and education, are not included.

The vector of displacement indicators (D_{ipt}) contains three types of variables: dummy variables that equal one in the years prior to the displacement, a dummy variable equal to one in the year that the father loses his job, and a series of dummy variables indicating that a displacement took place in a previous year. The first set of indicator variables captures the possibility that the father's wages may begin to deteriorate prior to the actual displacement. This might happen if wages are cut when the firm hits difficult times: failure to include these dummies would lead to a biased estimate of the effect of the displacement. Our model, therefore, includes a dummy variable for each of the four years we observe the father before the job loss occurs. The dummy variable indicating the year of the displacement captures its immediate effect on family resources, whereas the coefficients on the set of variables indicating that a displacement occurred in a previous year will reflect the persistence of the displacement effect

[3] The province fixed effect is determined in the initial year the father is observed (1978).

over time. We follow the post-displacement period for eight years, including a dummy variable indicating that eight or more years have elapsed since the displacement took place. An eight year reduction in family resources comprises a significant fraction of the time a child is growing up, though most of the children in our sample will no longer be living at home at the end of the eight year period.

The error term in the above equation contains a time-invariant family-specific effect, α_i, which measures average resources net of displacement. By including this fixed effect, we are able to separate variation in resources that is likely to be correlated with unobserved parental characteristics from variation due to a random shock. At the same time, the series of displacement dummies allows us to trace out the economic consequences in each year following the job loss and to estimate both the short-term and long-term effects, which may differ.

As will be discussed in Section III.B. the results from this exercise show that displacement substantively reduces family resources for many years. In order to facilitate our subsequent analyses, we will also estimate the effect of displacement using a version of equation (1) that replaces the individual fixed effect with the average of family income between 1978 and 1980 (which is at least two years before any displacements occur) and replaces the vector of displacement dummies with a single indictor for whether or not a displacement has occurred in the last five years or will occur in the next two years.

$$\ln I_{ipt} = Shock_{ipt}\delta + \phi AvgInc_{78-80} + u_{ipt} \qquad (2)$$

where $AvgInc$ is the family's (or father's) average income or earnings between 1978 and 1980, and $Shock$ is a dummy variable equal to 1 if a displacement occurs during the displacement window described above. The coefficient on the *Shock* dummy indicates the average effect of displacement on family income over the years we study. The estimates produced by equations 1-2 will inform us about the magnitude and persistence of the economic losses that result from displacement.

II.B. Estimating the Effect of Displacement on Children's Outcomes

After documenting that job loss leads to a large, persistent decline in resources, we next use information about whether a child's father lost his job to identify the effect of an income shock on children's long-term economic outcomes. In this part of our analysis, we regress a measure of the child's economic well-being on average family income between 1978 and 1980 and the *Shock* dummy.

$$O_i = a + bAvgInc_{78-80} + cShock_i + \varepsilon_i \qquad (3)$$

where O_i represents an economic outcome for child *i.* Thus we compare outcomes across children whose parents experienced a job loss to outcomes for those whose parents did not, controlling for family income in the pre-displacement years. We also include a number of additional control variables that will be discussed in the next section. They key to this identification strategy is the assumption that after controlling for average income before 1981, the families that experienced a displacement were ex ante no different from those who did not.

III. Data

Our analysis is based on data from the Intergenerational Income Database (IID), which is maintained by the Family and Labour Studies Division of Statistics Canada. The IID links tax information on children born between 1963 and 1970 to data on their parents, for all years between 1978 and 1999. The links were made possible using the T1 Family File (T1FF) of the Small Area and Administrative Data Division of Statistics Canada.

The T1FF is a data set of individual tax records that has been processed in a way that matches members of each tax filer's family. The primary way in which children are matched to their parents is through their name and address. In order to be identified as living in the same family, the child must file from the same address as the parent at least once during a five year period beginning when the child is 16-19 years of age. Evidence presented in Oreopolous (2003) suggests that this matching process picks up most adolescents in Canada. Over 80 percent of 20 year olds live with a parent, for example, and 73 percent of them receive non-transfer income. Younger children are more likely to be living at home, but less likely to file a tax return.[4] All Canadians must file a tax return if they pay income tax in that year, and if they claim unemployment insurance benefits, a nonrefundable tuition tax credit or the monthly deduction for enrollment in a full-time education program. Since a child need only file once over a five year period in order to be included in the sample, the vast majority of children make it into the IID. Oreopoulos reports that the database includes 72 percent of youth who were 16-19 in 1982, 1984 or 1986 (the years in which the matches took place).

The IID provides detailed administrative data on the incomes of children and their matched parents from 1978 to 1999. It also includes information on their age, gender, marital status, family composition, and residential address as well as an identification number for the firm at which the individual is employed. This ID number is used to match fathers in the IID to information about their firms from Statistics Canada's Longitudinal Employment Analysis Program database (LEAP). LEAP is a company-level database that includes all employers in Canada, both corporate and unincorporated. The database tracks the employment and payroll characteristics of individual firms from their year of entry to their year of exit.[5] Employers in Canada are required to register a payroll deduction account and issue a T4 slip to each employee that summarizes earnings received in a given fiscal year. The LEAP database includes every business that issues a T4 taxation slip.

Only those already in the IID are matched to the LEAP firm identification number. Firm size is calculated as the number of fathers in the same firm in a given year. An internal match to

[4] Note that a child may live away from home but still file from a parent's address, and thus be included in the IID. Children who are away at college fall into this category.

[5] Self-employed persons who do not draw a salary are not included on the LEAP database. In addition, businesses comprised solely of individuals or partnerships who do not draw a salary are also excluded from the LEAP.

the full LEAP database at Statistics Canada indicates the average ratio between total firm size and total father firm size for firms identified in the IID is 9.9. Thus, on average, the IID contains approximately a one-in-ten (non-random) sample of all employees in firms matched in both the IID and the LEAP database. Our sample also includes a 3 digit industry code for each firm and province location of firm's head office**.**

The longitudinal nature of the matched IID allows firm entry and exit to be identified on an annual basis. A firm closure is assigned in a given year if there are no IID fathers working at the firm in any following year (through 1999).[6] In order to distinguish true closures from company reorganizations that lead to new identification codes, however, we do not count a firm as being closed if 35% or more of its workers move to the same "new" firm.[7] We follow JLS in defining a mass layoff as a reduction in firm size (measured by the number of employees in the IID) of more than 35%.[8]

Out main sample is limited to individuals who were between the ages of 12 and 14 in 1982. Information on older children is available in the IID, but we do not include these children because they are likely to have left home shortly after the displacement occurred. Information on younger children is not available. Children whose fathers are missing tax data are eliminated because without the tax data we cannot observe fathers' earnings, place of employment or labor market status. This restriction reduces the sample of fathers by about 11 percent. We also restrict the sample to children whose fathers were between the ages of 30 and 50 in 1978. This ensures that we are focusing on fathers whose incomes would have been relatively stable: earnings of young workers tend to be more volatile than those of workers who are over 30, and Stevens

[6] This may lead to some misclassifications. For example, if a firm disappears in 1983, we will identify the closing year as 1982. In some cases, the firm may have closed early enough in 1983 that it did not file T-4 slips.
[7] We examined the sensitivity of the results around this threshold using alternative values of 15 and 50 percent. Coefficient estimates for the main tables were similar. The standard errors were somewhat larger for the 15 percent threshold.
[8] We examined the sensitivity of our results to this threshold. For example, we tried defining a mass layoff as a decline in firm size of more than 50 percent in firms with less than 20 fathers and a decline of more than 15 percent in firms that had more than 250 employees. The results were similar. As shown in the descriptive statistics tables, displacement effects are mostly being identified by firm closures.

(1997) shows that the long-term effects of displacement are largest for workers with more years of tenure.

We also restrict our main sample to fathers who are initially working at firms that employed between 5 and 500 men (in the IID). We require that the firm employ at least 5 fathers in order to reduce the possibility of mislabeling as displaced, men who voluntarily left small firms. An upper bound of 500 is chosen because closures at larger firms are extremely rare, and we were concerned that including such firms would introduce heterogeneity across the treatments and controls. Wage premiums are associated with large firms. Finally, we eliminate children whose fathers earned more than $1,000,000 in a single year, in order to be sure that our estimates are not driven by outliers.

The treatment group consists of 12 to 14 year olds whose fathers experienced a displacement in 1982. Our primary control group is consists of individuals whose fathers stayed with the firm through 1982, but who may have left after that. Fifty-six percent of fathers in this control group remained at the same firm until at least 1988.

Our analysis focuses on the effects of displacements that occurred in 1982. Choosing this date allows us to base our sample on the children of fathers who had at least four years of tenure at the firm, while maximizing the number of years the children would be likely to be living at home after the displacement occurs. Another advantage of focusing on displacements that occurred in 1982 is that it was the beginning of a substantial and prolonged recession in Canada.

The IID includes information on three socioeconomic outcomes: earnings, receipt of unemployment benefits, and receipt of social assistance. We use information that is available between 1995 and 1999 to create three dependent variables: the log of a five-year earnings average, an indicator for whether the individual received unemployment insurance during the five year period, and an indicator for whether the individual received social assistance during the five year period. Since earnings generally increase with age, we adjust our earnings measure by regressing it on a set of age dummies and use the residual as our dependent variable.

IV. Results

IV.A. Summary Statistics

Sample summary statistics are shown in Table 1. As described above, most of our analysis focuses on children whose fathers were employed at firms with between 10 and 500 employees. Our sample contains approximately 40,000 fathers, 2200 of whom experienced a mass layoff or firm closure in 1982. These men worked at approximately 7900 different firms, 464 of which either closed or engaged in a mass layoff during 1982.[9] Control fathers remained with the same firm between 1978 and 1982.

Table 1 shows separate statistics for our treatment and control groups. Fathers' average age, income and earnings are initially very similar across the two groups, but by 1988, six years after treatment fathers have lost their jobs, the labor market characteristics of the two groups are quite different. Average earnings of displaced fathers are roughly $45,000, while the average earnings of the control fathers are roughly $53,000. Not surprisingly, the displaced fathers are also much more likely to be receiving unemployment insurance.[10] Table 1 thus provides some initial evidence that firm closings and layoffs generate substantial shocks to a family's economic status. At the same time, these shocks do not appear to affect other family background characteristics:

Table 1 also shows that treatment and control children have different labor market outcomes. For example, average earnings between 1995 and 1998 are about $26,000 among those whose fathers experienced a job loss and $28,000 for those whose fathers did not. Similarly, treatment children have higher rates of UI and SA receipt than the controls.

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[9] The control group in the main sample may include fathers displaced after 1982. The fraction of displaced workers in the control, however, is likely to be small. We also considered an alternative control group that remained in the same firm between 1978 and 1988 and produced similar results with this group than with the control group we use here. The control group in our main sample is free to leave old and enter new firms, whether such a move occurs for positive or negative reasons.

[10] Information on social assistance receipt is not available prior to 1992.

The last column of Table 1 provides these descriptive statistics for all individuals in the IID who were 12-14 years old in 1982. As expected, the average size of the firm at which the fathers of these children work is smaller, while the maximum firm size is larger. Average family income is comparable, though slightly higher.

IV.B. The Monetary Costs of Displacement

In this section we document that displacement leads to a substantive long-term reduction in family resources. We begin by graphing the average earnings trajectories of treatment and control fathers. Our earnings measure is the residual from a regression of earnings on age and province/year fixed effects, which allows us to abstract from life-cycle trends and province-specific business cycles. Figure 1A makes clear that prior to 1982 the two groups experienced virtually identical earnings trajectories, lending weight to our hope that the treatment and control children come from similar backgrounds. At the same time we see that displacement produces a large and persistent shock to earnings. Both of these findings are necessary to our identification strategy. Figure 1B tells a similar story. Here we plot kernel density estimates of the earnings distributions for the two groups. The distributions are very similar prior to 1982, but after 1982 the distribution among displaced fathers is shifted substantially to the left.

We see a similar pattern when we look at receipt of UI receipt (Figure 1C).[11] As expected, displaced fathers experience a spike in benefit receipt in 1982, and by 1983, almost 40 percent of displaced father's are receiving UI benefits. UI use falls thereafter, but gradually, and never to the average levels of the non-displaced group. We also note that UI receipt rises in 1982 and 1983 among the control fathers. Some of these fathers may have been displaced from firms that did not meet our definition of a mass layoff or closure, or they may have claimed UI without being laid off.

[11] UI receipt is zero between 1978-1981, when the father was working at the same firm.

Figure 2 shows why it is important to confine our sample to children whose fathers worked at medium-sized firms. In this figure, we see that when we extend the sample to include fathers who worked at firms with more than 500 employees, pre-1982 earnings among the treatment and control groups no longer coincide. This may reflect the fact that very few large firms experience closings or layoffs: since these events are so rare among large firms, there may be more heterogeneity between workers who do and do not get laid off. Identification is based on the assumption that displacement is not correlated with cross-sectional differences in family background characteristics, so including children whose fathers worked at bigger and smaller firms could be problematic.

Table 2 presents the results from our regressions of fathers' annual earnings and income on the displacement dummies. Columns 1 through 3 show estimates based on equation (1) using father's earnings, father's income, and parental income as the dependent variables. Like previous studies, we find that family resources experience significant declines when a job loss occurs. For example, in the year following a job loss, father's earnings fall by 29%, father's income falls by 17%, and parental income falls by 14%.[12] [13] Family resources recover somewhat over time, but even 8 years later earnings are approximately 16% lower than they would have been if the displacement had not occurred. Similarly, the two income measures are reduced by 13 and 11 percent. These estimates are all statistically significant, and indicate that displacement produces substantive and persistent economic losses. They compare favorably to the estimates produced by JLS.

The first 3 rows of Table 2 also show what happens to family resources in the years prior to the displacement. As foreshadowed in Figure 1, there is no evidence that earnings or income begin to deteriorate prior to the job loss. The coefficient estimates are small and precisely

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[12] The percentage effect on earnings is computed as $e^{\delta} - 1$.

[13] A firm closure or mass layoff can occur anytime during the year. The fathers in our sample may, therefore, lose their job anytime between early January and late December. As a result, spells of unemployment and earnings losses may be larger in the year following the displacement than in the displacement year itself.

estimated. This suggests that pre-displacement income can be included in our subsequent analysis as a control for permanent income.

The last three columns of Table 2 provide the estimates produced by estimation of equation (2). This paired-down version of equation (1) summarizes the monetary effect of displacement in a single coefficient, which is convenient for the second stage of the analysis.[14]

IV.C. Intergenerational Effects of Displacement

Having established that displacement substantially reduces family resources, we now investigate whether it produces intergenerational effects. Table 3 displays the results from this "second stage" of our analysis. Dependent variables include the log of average earnings between 1995 and 1999, a dummy variable indicating whether the child filed for unemployment benefits between 1995 and 1999, and a dummy variable indicating whether she filed for social assistance between 1995 and 1999.

Column 1 shows the results produced by an OLS regression of the log of child's earnings on the log of father's income between 1978 and 1981. Sample variation in this variable is likely to reflect variation in other family background characteristics though Figure 1 suggests that characteristics correlated with family income are unlikely to differ much between the treatment and control children. The estimated coefficient of 0.37 is consistent with the intergenerational correlations literature, which generally finds that the correlation between American fathers' and sons' earnings is about 0.4.

In the next column we include only a dummy variable indicating whether the father lost his job due to a mass layoff or plant closing. This variable has a powerful effect on the child's

[14] The estimates presented in Table 2 could be biased if displaced workers have unobserved characteristics that not only lower their earnings levels, but also their rate of earnings growth. In order to address this concern, we have also re-estimated equation (1) including father-specific time trends (equation 2). The results are very similar. Since the inclusion of person-specific trends does not appear to alter our estimates, we exclude these trends from the rest of our analyses.

earnings, which are 11% lower than the earnings of those whose fathers were not displaced. Remarkably, this estimate barely changes even when we control for father's pre-1981 income (column 3). Furthermore, the point estimate on the log of pre-1981 income is robust to the inclusion of the displacement dummy. Taken together, these results suggest that our treatment and control groups are well-matched.

Column 4 adds firm-level controls to our model, including a quartic in father's firm size, and 10 industry fixed effects. .If the inclusion of these controls alters the estimated displacement coefficient then we should be concerned about the possible influence of family background characteristics. We also include 38 dummies indicating region of residence, since mass layoffs and firm closings that occur in company towns may have long lasting effects on local labor market conditions (Flint, Michigan comes to mind). If individuals tend to stay in the same location where they grew up then the displacement coefficient may partly reflect the fact that mass layoffs and firm closings depress wages in the local economy. Evidence presented in Page and Solon (2003) suggests that individuals have a strong tendency to live near where they were raised. The estimated displacement coefficient is not changed by the addition of these controls, however.

The remainder of Table 3 shows what happens when we replace the dependent variable with indicators for whether the child received unemployment benefits or social assistance. These specifications also suggest that children whose parents experienced a job loss have worse economic outcomes than those whose parents did not. We find that children whose fathers were displaced are two percentage points more likely to receive unemployment benefits (though this is not statistically significant), and 3 percentage points more likely to receive social assistance as adults than those whose fathers remained at the same firm through 1982. The mean level of social assistance receipt in the second generation is 0.06, so this estimated effect is very large.

If we assume that all of the displacement effect works through the decline in family resources then we can use the estimates in Table 3 to approximate the implied effect of a dollar reduction in family income on a child's subsequent earnings**.** Table 2 suggests that the average effect of father's displacement on his own log earnings is approximately .15. The corresponding reduction in the second generation's earnings is .10. This suggests that a one dollar reduction in father's permanent earnings leads to a subsequent reduction in his son's earnings of 66 cents. This is a very large effect, although the standard error estimate is also very large, so the confidence interval around this estimate contains both much larger and much smaller estimates.

Nevertheless, it is worth considering what might be driving such a large estimate. One possibility is that displacement has an effect on the family that goes beyond the effect of the monetary loss itself. Job loss is likely to lead to higher levels of parental stress, for example, which may be transmitted to children. Lower income levels or subsequent re-employment could also be associated with residential moves, which are thought to have a negative impact on children (McLanahan and Sandefur, 1994). We investigate these possibilities in Table 4. While we cannot directly observe parental stress, se can look at whether displacement affects the probability of divorce and at how it affects residential mobility. We can also examine whether the inclusion of these variables affects the estimated effect of displacement on children's outcomes.

Column 1 provides no evidence that fathers who lost their jobs are more likely to be divorced than fathers who did not lose their jobs. We do see effects on residential mobility, however. Compared to children whose fathers are able to keep their jobs, displaced children are about 3 percentage points more likely to move. The last two columns of the table show what happens to the displacement coefficient when these variables are added to regressions in which the child's outcome is the dependent variable.

An alternative way of investigating this issue is to add the log of average earnings between 1982 and 1988 to our basic specification:

$$O_i = \beta_1 + \beta_2 AvgInc_{78-80} + \beta_3 AvgInc_{82-88} + \beta_4 Shock_i + \varepsilon_i \ . \qquad (4)$$

The estimates of β_3 and β_4 allow us to separate the displacement effect into an income component and a part that is unrelated to income. The results of this exercise, which are displayed in Table 5, suggest that the displacement effect is driven almost entirely by changes in income. The inclusion of post-displacement income leads to a dramatic fall in the estimated displacement coefficient, which is no longer statistically different from zero. At the same time, the estimated effect of post-displacement income on child's earnings is substantive. One needs to be careful in interpreting this coefficient because differences in father's 1983-1988 income, controlling for displacement, may be driven by variation in unobserved characteristics. The estimates do not suggest that the displacement estimates presented in Table 3 is driven by non-monetary effects, however.

Next, we consider how the displacement effects vary across the income distribution. Since both the financial constraints and associated stress that accompany a job loss are likely to be larger for low income families, we expect that the intergenerational displacement effects will be largest for individuals who grew up in less affluent families.[15] An advantage of basing our analysis on such a large dataset is that we can investigate this issue directly. In Table 6 we present displacement estimates separately by the family's (initial) income quartile. The displacement effects appear to be concentrated entirely among those families for whom father's earnings are in the lowest quartile. Among children in this group subsequent earnings are 11% lower than they would have been if the father had not been displaced, and the probability of social assistance receipt is 2 percentage points higher. In contrast, there is no evidence that there is any intergenerational effect among families that had higher incomes. This finding may provide some insight as to why previous studies have failed to find the presence of income effects: small sample sizes make it difficult to estimate nonlinear effects, yet most of the action appears to be at the bottom of the income distribution.

[15] For example, Coelli (2004) finds that low income teenagers whose parents experience a job loss are less likely to attend college.

IV.D. Robustness Checks

In the remainder of the paper we discuss several exercises that are designed to examine the sensitivity of our results to model specification and variable definitions. First, we investigate whether job losses that occur after children have left home have the same intergenerational effects as those that occur when the children are younger. A father's displacement should have a smaller psychological and financial effect on individuals who are no longer living in the household, so estimates of the same magnitude may be a sign that the displacement coefficient is picking up the effects of unobserved family background characteristics.

There are two ways in which we investigate this possibility: by extending our basic sample to include older children, and by aging our sample of children to 1989 and estimating the intergenerational effects of parental displacements that occur in that year. By 1989 our sample of children is between the ages of 19 and 21 and should be less sensitive to a parental job loss. Table 7 shows what happens when we add older children to our original sample and re-estimate equation (3) by age group. As in Table 3, individuals who were between the ages of 12 and 14 at the time of the job loss have lower adult earnings than they would have had if the displacement had not occurred. In contrast, there is no evidence that parental job loss leads to any long lasting effects among older children. The standard error estimates are often quite large, but the pattern of the point estimates is consistent with our expectation that intergenerational effects are mostly experienced by children who continue living in the household for several years after the shock.

In Table 8 we see the estimated effects of parental displacements that occurred in 1989. Labor market outcomes are measured for the same cohorts of children whom we followed in Table 3, but by 1989 these children were 19-21 years old and mostly living apart from their parents. As in Table 3, children's earnings and benefit receipt are measured between 1995 and 1999. Unlike Table 3, however, we see no evidence that parental job loss affects the next generation's outcomes: the estimated coefficient on the displacement variable is -0.033, which is much lower than the estimated displacement effect at younger ages, and it is not statistically different from zero. Similarly, the estimated effect on children's social assistance receipt is not statistically significant. This finding is particularly noteworthy because father's earnings losses following a 1989 displacement are even larger than those following a job loss in 1982: fathers who were displaced in 1989 experience short term earnings declines that are nearly double those experienced by fathers who lost their jobs in 1982.

Next, we examine the sensitivity of our results to the way in which we have defined our control group. In the main analysis, control fathers may leave their place of employment any time after 1982, but this means that some of them probably end up experiencing displacements in later years. Another possibility is to restrict the control group to children whose fathers remained with the same firm throughout the observation period. In Table 9 we show the results from an analysis in which control fathers who left their firm before 1988 are dropped from the sample. We find that placing these more stringent requirements on the control produces slightly larger estimates.

We have also repeated the analysis separately for boys and girls. While the results are not shown, they are very similar to those for the full sample, though the point estimates for girls are much less precisely estimated. The noisiness of the girls' estimates is undoubtedly driven by the fact that many women in their 20's and 30's choose not to work, or to work fewer hours while they are raising children, and not because they have poor labor market options. Women with no earnings between 1995 and 1999 are not observed.

V. Conclusions

This paper provides new evidence on mechanisms that are behind the transmission of economic status across generations. While the existence of large intergenerational income correlations has lead many researchers to conclude that family income is an important determinant of children's eventual economic success, the evidence in support of this hypothesis is surprisingly limited. Previous research has been hampered by small sample sizes and the difficult task of controlling for unobserved parental attributes. Because we exploit longitudinal variation that is induced by mass-layoffs and firm closings we are able to separate the effect of a long-lasting income shock from the effect of innate parental attributes. Our access to a dataset that contains over 100,000 father/son pairs aids our ability to identify this effect.

We find that the adult earnings of children whose fathers were displaced are xx% lower than earnings of similar individuals whose fathers did not experience an employment shock, even after we account for fathers' pre-displacement earnings, initial region of work, industry and firm size. Relative to children whose fathers did not lose their jobs, children of displaced workers are also more likely to receive unemployment insurance and social assistance. Our estimates are driven almost exclusively by the experiences of individuals whose family income during childhood was in the bottom quartile of the income distribution. We estimate smaller effects on individuals who were older than 16 at the time of the father's displacement, and no effects at all on individuals who were older than 19. The results suggest that the long term consequences of unexpected job loss extend beyond the effect on one's own income to the eventual labor market outcomes of one's children.

The interpretation of these results relies on the plausibility of the control group. Our analysis assumes that the labor market experiences of control fathers provide an appropriate counterfactual for what would have happened to the treatment fathers if the displacement had not occurred. Put differently, we assume that conditional on 1978-1981 earnings and the other control variables, the likelihood that a job loss occurs is the same for the treatment and control groups. The fact that pre-displacement labor market characteristics are virtually identical for the two groups is a promising sign that we have successfully controlled for innate family background characteristics, but if treatment and control families differ in ways that affect the second generation's economic outcomes without affecting the economic outcomes of the parents, then our displacement effects will not be identified. It is hard to imagine what such characteristics would be, however.

Finally, it is important to note that our estimation strategy captures the full effect of displacement. We have demonstrated that job loss leads to large, long lasting reductions in a family's monetary resources, but it may also impose non-monetary costs on the family that affect the children's long-run outcomes. Our identification approach allows us to control for fixed family background characteristics which enables us to identify the total effect (monetary and non-monetary) of a permanent income shock.

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Table 1A
Descriptive Statistics, Firms

	Treatment	Closures	Layoffs	Controls	All Children in IID 12 to 14
Average Firmsize	39	39	41	38	16
	(35)	(24)	(63)	(43)	(137)
Minimim Firmsize	5	5	5	5	1
Maximim Firmsize	493	493	484	500	9512
Average Median Wage	40,225	40,079	40,624	40,823	38,505
	(10,906)	(10,986)	(10,667)	(14,361)	(15,502)
Province					
Newfoundland	4.2	4.6	3.3	1.4	1.4
Prince Edward Island	0.0	0.0	0.0	0.4	0.5
Noval Scotia	2.5	1.4	6.6	2.7	3.1
New Brunswick	3.9	2.8	8.2	2.8	2.5
Quebec	28.3	29.5	23.0	28.8	30.5
Ontario	44.9	43.8	49.2	48.6	45.5
Manitoba	1.8	1.8	1.6	3.2	3.5
Saskatchewan	2.5	3.2	0.0	1.8	2.3
Alberta	9.5	9.7	8.2	7.0	7.2
British Columbia	2.5	3.2	0.0	3.4	3.6
1-Digit Industry					
Missing	0.4	0.5	0.0	0.1	0.1
Agriculture	6.7	6.9	6.6	3.7	3.2
Primary Textiles and Leather	3.5	3.7	1.6	8.8	7.2
Clothing and Furniture	7.8	6.9	11.5	10.6	10.6
Manufacturing	16.6	13.8	24.6	18.8	16.6
Construction and Transportation	21.8	19.7	29.5	20.2	21.0
Wholesale Trade	8.1	7.3	11.5	10.0	11.4
Retail Trade	9.2	11.5	1.6	6.4	9.2
Finance and Insurance	15.5	16.5	11.5	10.0	9.8
Education and Health Services	2.5	3.2		7.0	5.9
Accomodation, Food and Bev.	8.1	10.1	1.6	4.5	5.1
Number of Firms	464	374	82	7,916	18,805

Sample consists of all father-child pairs for which the child was between 12 and 14 in 1982 and the father worked a a firm with between 5 and 500 fathers in the IID. Fathers must have worked at the same firm for four years (between 1978 and 1981) and received no unemployment insurance between that time. The 'Treatment' sample includes fathers displaced from a firm that closes in 1982 or experiences a mass-layoff that year. Standard Deviations are in parenthesis.

Some examples of 3-digit categories:

032 Services Incidental to Fishing
033 Trapping

151 Tire and Tube Industry
152 Rubber Hose and Belting Industry
159 Other Rubber Products Industries

541 Apparel Wholesale
541 Electical and Electronic Household Appliance and Parts, Wholesale

911 Hotels, Motels, and Tourist Courts
912 Lodging Houses and Residential Clubs
913 Camping Grounds and Trailer Parks

Table 1B
Descriptive Statistics, Fathers and Children

	Treatment	Closures	Layoffs	Controls	All Children in IID
			Fathers, 1978		
Father's Age	37	37	38	37	37
	(5)	(5)	(5)	(5)	(5)
Father's Earnings	45,229	44,990	45,661	45,352	46,517
	(15406)	(16133)	(13998)	(15030)	(15840)
Father's Total Income	45,769	45,536	46,190	46,548	47,140
	(15,035)	(15,700)	(13,754)	(14,858)	(15,707)
Father on UI	0	0	0	0	0
Father Sample Size	1,849	1,190	659	33,767	64,559
			Fathers, 1988		
Father's Age	47	47	48	47	47
	(5)	(5)	(5)	(5)	(5)
Father's Earnings	45,282	44,524	46,652	52,901	53,343
	(30,569)	(31,464)	(28,856)	(69,996)	(61,164)
Father's Total Income	46,632	45,754	48,232	53,469	53,915
	(29,647)	(30,482)	(28,015)	(68,067)	(59,296)
Father on UI	0.13	0.14	0.12	0.05	0.05
	(0.34)	(0.34)	(0.32)	(0.23)	(0.22)
			Children, 1999		
Child's Income	25,818	25,268	26,854	27,646	27,768
	(20,144)	(19,878)	(20,611)	(47,274)	(38,941)
Child's Age	30	30	30	30	30
	1	1	1	1	1
Child on UI	0.23	0.24	0.22	0.22	0.22
	(0.42)	(0.43)	(0.41)	(0.41)	(0.41)
Child on Welfare	0.08	0.09	0.07	0.06	0.06
	(0.27)	(0.28)	(0.24)	(0.23)	(0.23)
Number of Children	2,171	1,340	831	38,931	71,534

Sample consists of all father-child pairs for which the child was between 12 and 14 in 1982 and the father worked at a firm with between 5 and 500 fathers in the IID. Fathers must have worked at the same firm for four years (between 1978 and 1981) and received no unemployment insurance between that time. The 'Treatment' sample includes fathers displaced from a firm that closes in 1982 or experiences a mass-layoff that year. Standard Deviations are in parenthesis.

Table 2
Effects of Displacement on Father's Real Log Earnings, Log Income and Mobility

	(1)	(2)	(4)	(5)
	Dependent Variable			
	Log Father's Earnings	Log Father's Income	Log Father's Earnings	Log Father's Income
Lead or Lag				
-3	0.006	0.005		
	[0.008]	[0.008]		
-2	0.003	0.003		
	[0.007]	[0.006]		
-1	0.005	0.004		
	[0.007]	[0.007]		
0	-0.122	-0.067		
	[0.011]***	[0.008]***		
+1	-0.289	-0.172		
	[0.020]***	[0.013]***		
+2	-0.188	-0.149		
	[0.015]***	[0.013]***		
+3	-0.192	-0.149		
	[0.018]***	[0.014]***		
+4	-0.199	-0.162		
	[0.020]***	[0.018]***		
+5	-0.166	-0.142		
	[0.018]***	[0.016]***		
+6	-0.147	-0.12		
	[0.019]***	[0.017]***		
+7	-0.142	-0.116		
	[0.020]***	[0.017]***		
+8	-0.155	-0.128		
	[0.022]***	[0.019]***		
Log Earnings 1978-81			1.03	0.99
			(0.01)	(0.01)
Displacement			-0.12	-0.10
			(0.01)	(0.01)
Observations	497546	498516	497546	498516
R-squared	0.55	0.59	0.35	0.40

Columns 1 and 2 show regressions using as dependent variables log father's annual earnings and log total income (both demeaned by age and year). The regressors are individual fixed effects and indicator variables for years since job displacement for fathers in firms that closed or experienced mass layoffs (the omitted category is not displaced or displacemed in at least 3 years. Columns 3 and 4 show results from regressing the same dependent variables on average log earnings between 1978 and 1981, and a dummy variable for whether a father is displaced in 1982. Asterix indicate significant at the 1% level.

Table 3
Estimated Effects of Father's Displacement on Child's Earnings, Unemployment and Social Assistance Receipt

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Age Adj. Log Earnings, 1995-99	Age Adj. Log Earnings, 1995-99	Age Adj. Log Earnings, 1995-99	Age Adj. Log Earnings, 1995-99	UI Receipt	Social Assistance Receipt
Father's Log Income Residual	0.367		0.366	0.354	-0.043	-0.071
	[0.029]***		[0.029]***	[0.031]***	[0.008]***	[0.005]***
Father Displaced		-0.114	-0.108	-0.124	0.015	0.028
		[0.036]***	[0.036]***	[0.037]***	[0.011]	[0.008]***
With Initial Firm Characteristic Controls	No	No	No	Yes	Yes	Yes
Observations	39,793	39,793	39,793	39,793	41,102	41,102
R-squared	0.03	0.04	0.04	0.05	0.05	0.01

Notes: The dependent variable in columns 1-4 is child's log real earnings averaged between 1995 and 1999 after de-meaning by age. All regressions include fixed effects for birth cohort interacted with gender. The initial firm characteristic controls include fixed effects for regional location of firm (18 possible characters that identify provinces and smaller regions in large provinces) interacted with an indicator variable for whether the firm is in an urban or rural location. The controls also include 11 industry categories and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 3B
Estimated Effects of Father's Displacement
Matched Displaced/Not-Displaced Father Sample

	(1)	(2)	(3)	(4)	(5)
Dep var:	Log Earnings Residual	Log Earnings Residual	Log Earnings Residual	UI Receipt	Social Assistance Receipt
Father's Log Income Residual	0.376 [0.040]***		0.37 [0.040]***	-0.027 [0.014]*	-0.055 [0.008]***
Father Displaced		-0.132 [0.039]***	-0.113 [0.039]***	0.022 [0.014]	0.033 [0.008]***
With Initial Firm Characteristic Controls	No	No	No	No	No
3 Digit Industry, 18-Category Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	12,711	12,730	12,711	13,134	13,134
R-squared	0.09	0.09	0.09	0.09	0.06

Notes: The sample includes only displaced fathers matched to at least one father not displaced from a firm in the same 18-category region and 3-digit industry. The dependent variable in columns 1-4 is child's log real earnings averaged between 1995 and 1999 after de-meaning by age. All regressions include fixed effects for birth cohort interacted with gender. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 3C
Estimated Effects of Father's Displacement
Matched Displaced/Not-Displaced Father Sample

	(1)	(2)	(3)	(4)	(5)
Dep var:	Log Earnings Residual	Log Earnings Residual	Log Earnings Residual	UI Receipt	Social Assistance Receipt
Father's Log Income Residual	0.338 [0.069]***		0.325 [0.069]***	-0.042 [0.023]*	-0.07 [0.014]***
Father Displaced		-0.118 [0.051]**	-0.098 [0.051]*	0.022 [0.017]	0.027 [0.010]***
With Initial Firm Characteristic Controls	No	No	No	No	No
3 Digit Industry, Region 18 Region, 5-Cat. Firm Size Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5919	5927	5919	6133	6133
R-squared	0.14	0.13	0.14	0.13	0.09

Notes: The sample includes only displaced fathers matched to at least one father not displaced from a firm in the same 5-category father firm size (<5, 2-9, 10-19, 20-39, 40-100, 100+), the same 18-category region and the same 3-digit industry. The dependent variable in columns 1-4 is child's log real earnings averaged between 1995 and 1999 after de-meaning by age. All regressions include fixed effects for birth cohort interacted with gender. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 4
Estimated Effects of Father's Displacement
On the Probability of Divorce, Residential Moves, and Mother's Income

	Dependent Variable		
	Divorced	Moved	Mother's Earnings
Lead or Lag			
-3	-0.001	0.01	-0.068
	[0.002]	[0.008]	[0.053]
-2	0.002	0.017	-0.114
	[0.003]	[0.010]*	[0.067]*
-1	0.004	0.008	-0.091
	[0.004]	[0.011]	[0.072]
0	0.003	0.021	-0.031
	[0.004]	[0.011]*	[0.078]
+1	0.003	0.028	-0.026
	[0.004]	[0.012]**	[0.079]
+2	0.002	0.03	-0.002
	[0.005]	[0.012]**	[0.085]
+3	-0.002	0.029	0.009
	[0.004]	[0.012]**	[0.086]
+4	0.001	0.025	-0.041
	[0.005]	[0.012]**	[0.088]
+5	0.005	0.029	-0.146
	[0.005]	[0.012]**	[0.091]
+6	0	0.025	-0.179
	[0.005]	[0.012]**	[0.094]*
+7	-0.003	0.018	-0.149
	[0.005]	[0.012]	[0.095]
+8	0.001	0.018	-0.066
	[0.005]	[0.012]	[0.098]
Observations	499,212	500,695	500,695
R-squared	0.48	0.65	0.74

Columns 1 and 2 show regressions using as dependent variables log father's annual earnings and log total income (both demeaned by age and year). The regressors are individual fixed effects and indicator variables for years since job displacement for fathers in firms that closed or experienced mass layoffs (the omitted category is not displaced or displacemed in at least 3 years. Columns 3 and 4 show results from regressing the same dependent variables on average log earnings between 1978 and 1981, and a dummy variable for whether a father is displaced in 1982. Asterix indicate significant at the 1% level.

Table 5
Effects of Father's Income and Father Displacement
on Child's Earnings, Unemployment and Social Assistance Receipt
Controlling for Father' Income 1983-1988

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Log Earnings Residual	Log Earnings Residual	UI Receipt	UI Receipt	Social Assistance Receipt	Social Assistance Receipt
Father's Log Income Residual, 1978 - 1981	0.354 [0.031]***	0.166 [0.043]***	-0.043 [0.008]***	-0.017 [0.011]	-0.071 [0.005]***	-0.033 [0.007]***
Father's Log Income Residual, 1983 - 1988		0.20 [0.027]***		-0.027 [0.007]***		-0.039 [0.005]***
Father Displaced	-0.124 [0.037]***	-0.034 [0.037]	0.015 [0.011]	0.01 [0.011]	0.028 [0.008]***	0.011 [0.008]
With Initial Firm Characteristic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,793	39,793	41,102	41,102	41,102	41,102
R-squared	0.04	0.05	0.05	0.05	0.01	0.02

Notes: The dependent variable in columns 1-2 is child's log real earnings averaged between 1995 and 1999 after de-meaning by age. All regressions include fixed effects for birth cohort interacted with gender, and firm characteristic controls for regional location of firm industry and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 6
Effects of Father's Income and Father Displacement on Child's Earnings, Unemployment and Assistance Receipt by Father's Income Quartile in 1978

Income Quartile:	(1)	(2)	(3)	(4)
Dependent var:	**Log Earnings**			
Father's Log Income	0.445	0.418	0.228	0.294
	[0.144]***	[0.254]*	[0.204]	[0.085]***
Father Displaced	-0.258	-0.148	-0.041	-0.02
	[0.088]***	[0.078]*	[0.068]	[0.059]
	Receipt of UI			
Father's Log Income	0.055	0.002	-0.003	-0.147
	[0.017]***	[0.088]	[0.082]	[0.031]***
Father Displaced	0.030	0.030	-0.017	0.011
	[0.024]	[0.023]	[0.022]	[0.023]
	Receipt of Social Assistance			
Father's Log Income	-0.009	-0.105	-0.046	-0.060
	[0.012]	[0.056]*	[0.047]	[0.015]***
Father Displaced	0.037	0.038	0.016	0.004
	[0.016]**	[0.014]***	[0.016]	[0.013]

Notes: The sample of fathers are split by income quartile based on average income between 1978 and 1981. The table shows results from regressions run separately by father's income quartile. All regressions include fixed effects for birth cohort interacted with gender, and firm characteristic controls for regional location of firm industry and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics

Table 7
Effects of Father's Income and Father Displacement
on Child's Log Earnings, by Age at Father's Displacement

Base Sample: Firm Size between 5 to 500 Fathers

	Age at Father's Displacement							
	12	**13**	**14**	**15**	**16**	**17**	**18**	**19**
Father's Residual Log Income	0.352	0.361	0.279	0.318	0.312	0.323	0.332	0.336
	[0.064]***	[0.061]***	[0.037]***	[0.033]***	[0.032]***	[0.031]***	[0.028]***	[0.026]***
Father Displaced	-0.131	-0.053	-0.173	-0.077	-0.043	-0.02	-0.033	-0.013
	[0.068]*	[0.056]	[0.068]**	[0.054]	[0.048]	[0.047]	[0.041]	[0.041]
Number of Obs.	10864	12939	15990	19711	22483	28161	35244	40247

Notes: The table shows results from regressions run separately by child's age when fathers are displaced. All regressions include fixed effects for birth cohort interacted with gender, and firm characteristic controls for regional location of firm industry and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 8
Effects of Father's Displacement in 1989
on Son's Earnings, Unemployment and Assistance Receipt
Father Displaced when Son Aged 19 to 21

	Log Son's Earnings Earnings	Receipt of UI	Receipt of SA
Father's Residual Log Income	0.272 [0.026]***	-0.06 [0.007]***	-0.041 [0.004]***
Father Displaced	0.019 [0.033]	-0.004 [0.018]	0.006 [0.009]
Number of Obs.	40001	40618	40618

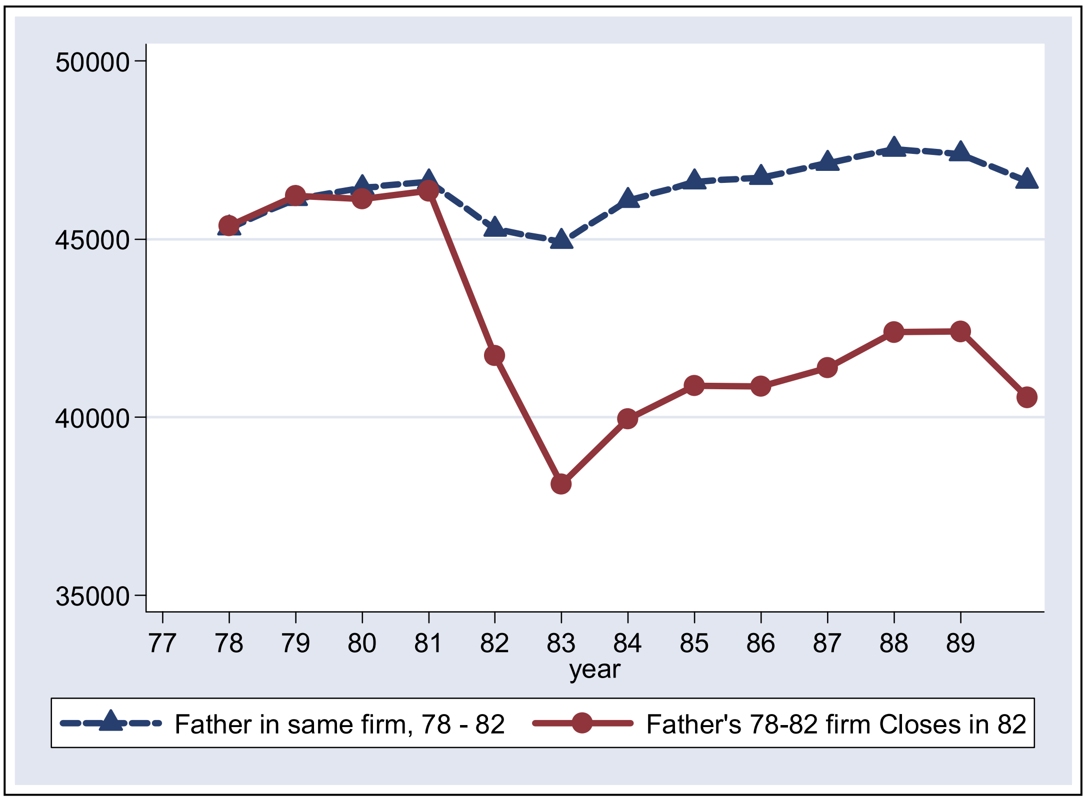
Notes: All regressions include fixed effects for birth cohort interacted with gender, and firm characteristic controls for regional location of firm industry and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Table 9
Effects of Father's Displacement on Child's Earnings, UI and Social Assistance Receipt Using Alternative Control Group

	Log Son's Earnings	Receipt of UI	Receipt of SA
Father's Residual Log Income	0.331	-0.055	-0.065
	[0.035]***	[0.013]***	[0.008]***
Father Displaced	-0.166	0.017	0.04
	[0.038]***	[0.012]	[0.008]***
Number of Obs.	16,435	16,944	16,944
R-squared	0.04	0.05	0.02

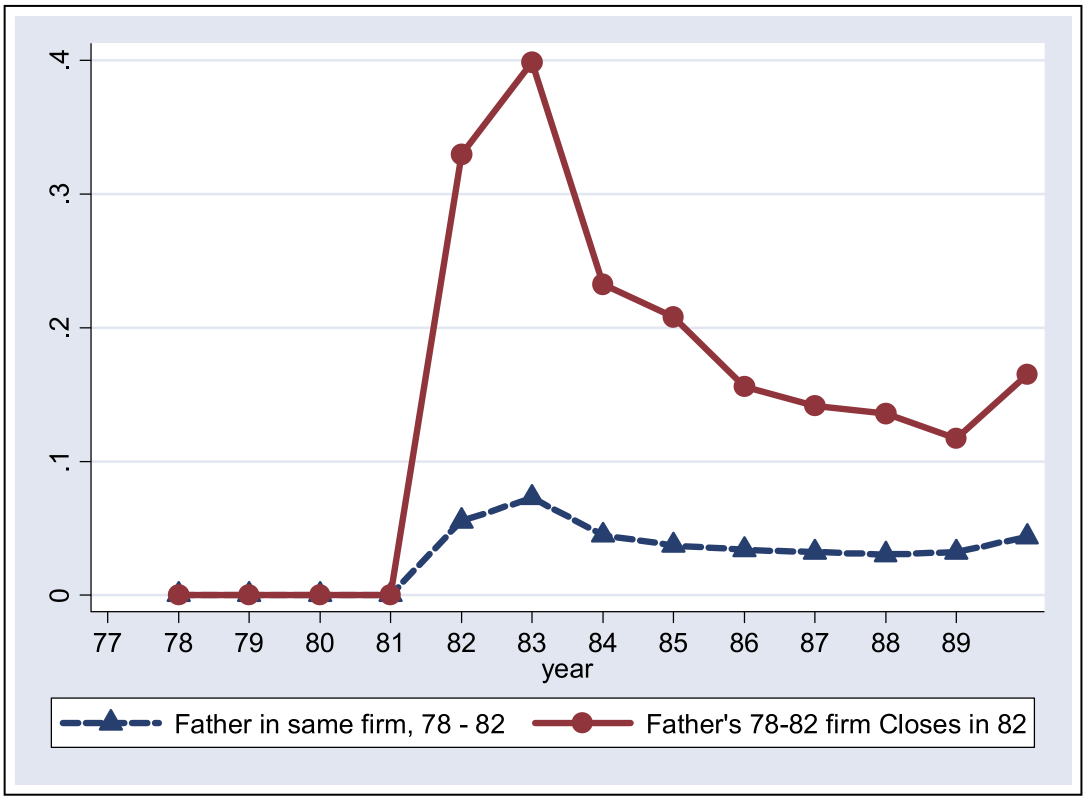
Notes: All regressions include fixed effects for birth cohort interacted with gender, and firm characteristic controls for regional location of firm industry and the median log wage of the initial firm in 1978. Huber-White standard errors are shown from clustering by father ID. Single, double, and triple asterix indicate significant coefficients at the 10 percent, 5 percent, and 1 percent levels respectively. See text for more data specifics.

Figure 1A
Annual Average Father's Income
by Whether Firm Worked at between 1978 and 1982 Closed in 1982/83
Number of Father's at Initial Firm between 10 and 500



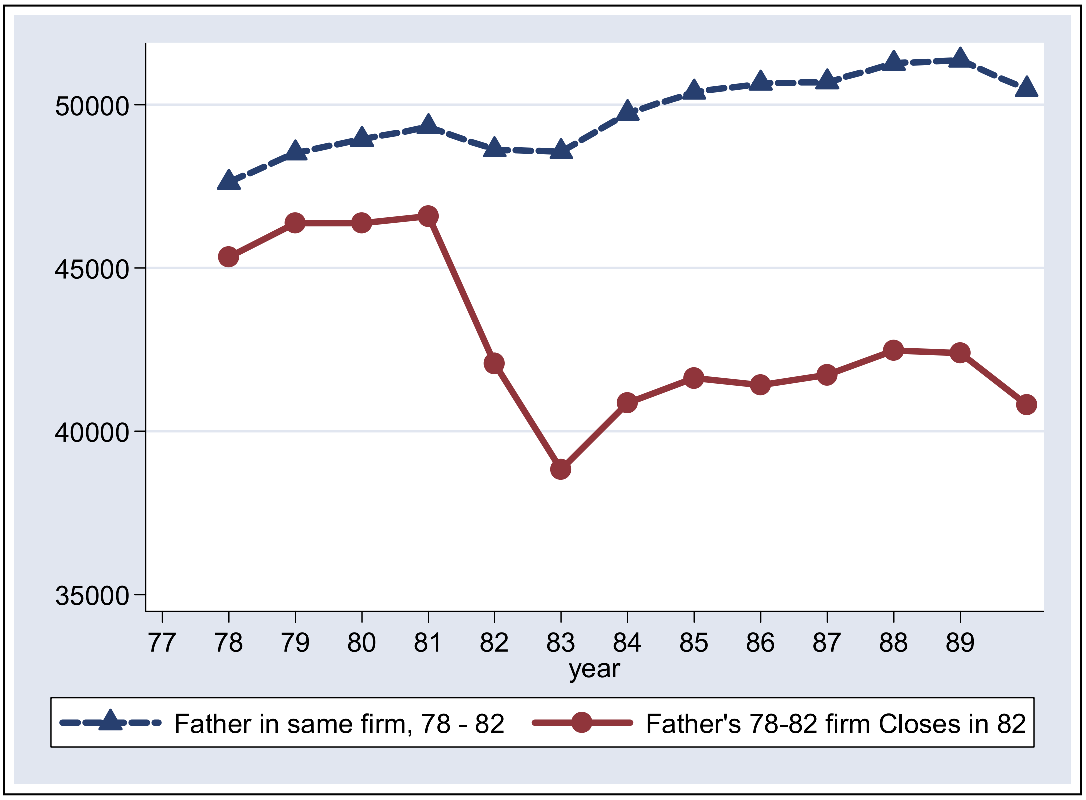
Notes:

Figure 1B
Annual Average of Unemployment Insurance Receipt
by Whether Firm that Father Worked at between 1978 and 1982 Closed in 1982/83
Number of Father’s at Initial Firm between 10 and 500



Notes:

Figure 2
Annual Average Father's Income
by Whether Firm Worked at between 1978 and 1982 Closed in 1982/83
Number of Father's at Initial Firm at least 5



Notes:

Figure 3: Kernel Density of Father's Earnings by Displacement Status in 1982/83, 1978-89

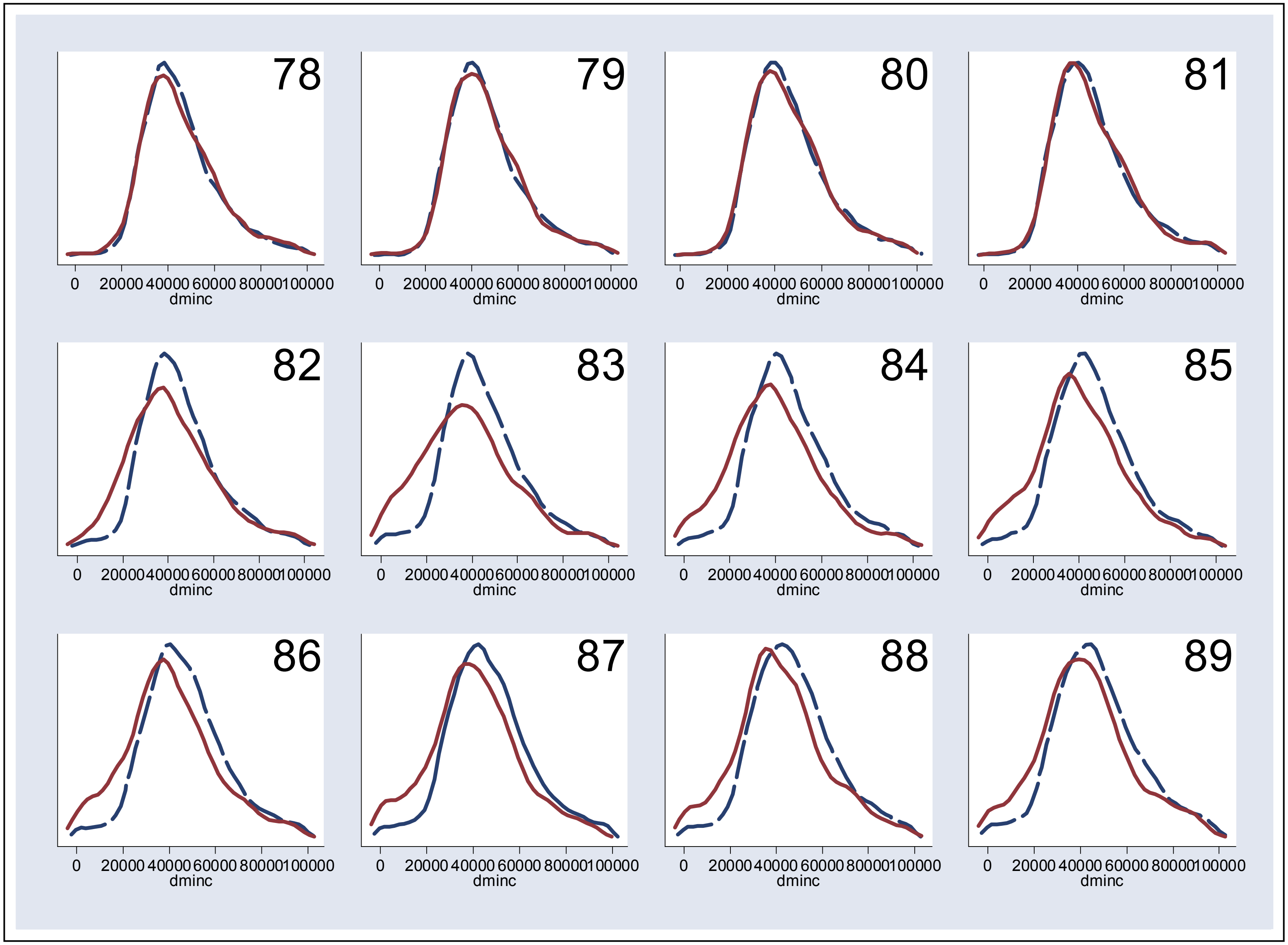
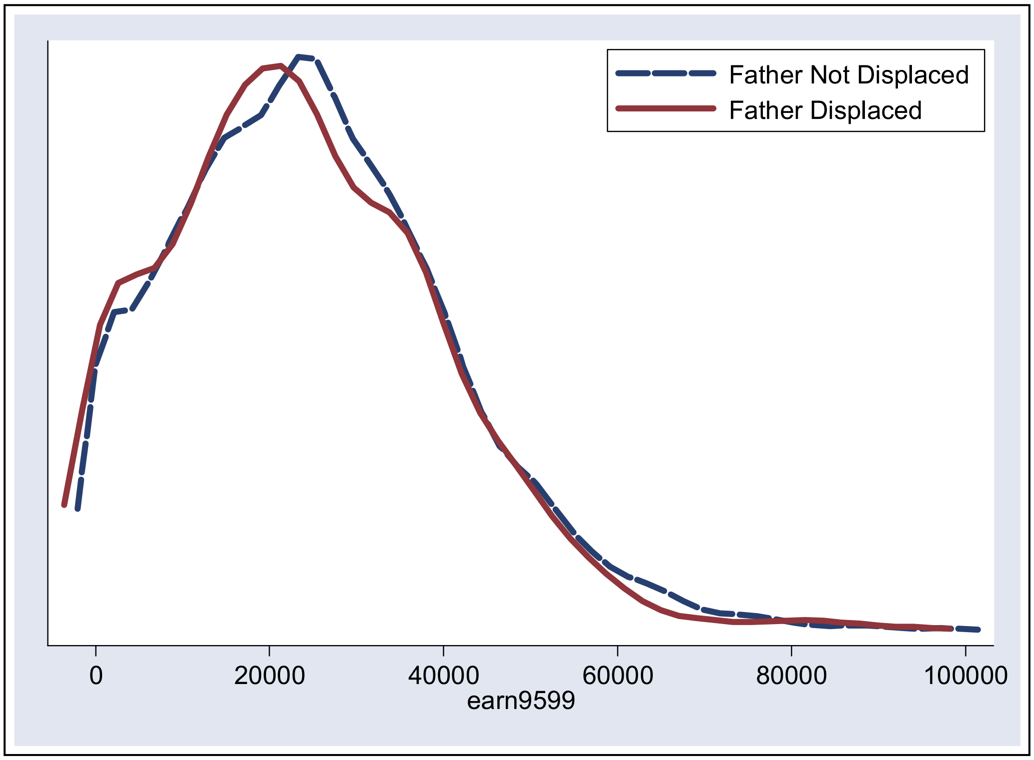


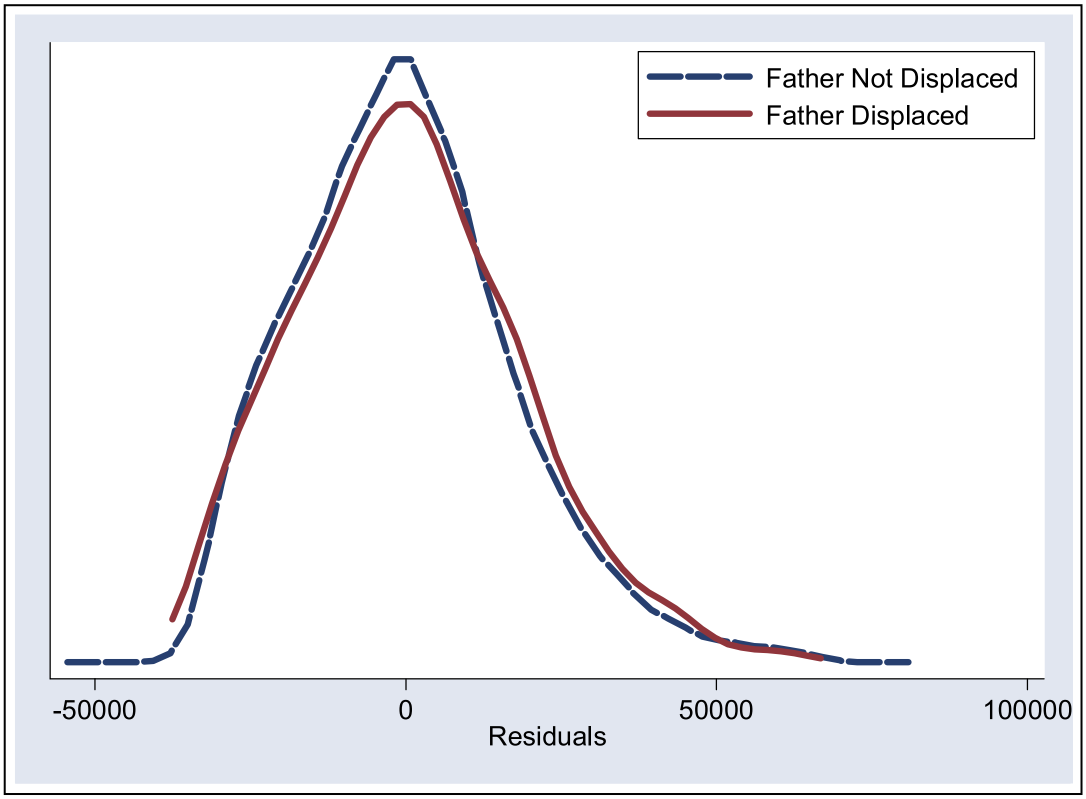
Figure 4
Kernel Density of Son's Average 1995-99 Earnings
by Father's Displacement Status in 1982/83



Notes:

Mean Difference: Displaced Group – Non-Displaced Group = - 1,389
p-value from t-test for hypothesis means the same = 0.012
p-value from kmogorov-smirnov test for hypothesis distributions the same = 0.019

Figure 5
Kernel Density of Son's Average 1995-99 Residual Earnings
by Father's Displacement Status in 1989/90
Son Ages 19 to 26 in Year of Displacement



Notes:

Mean Difference: Displaced Group – Non-Displaced Group = 518
p-value from t-test for hypothesis means the same = 0.562
p-value from kmogorov-smirnov test for hypothesis distributions the same = 0.736

Figure 6: Residual Son's Earnings by Age at 1982 and Father's Displacement Status