Family Ties and Worker Displacement*

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Abstract

Young adults, aged 25 to 35, who live close to their parents experience stronger earnings recoveries after a job displacement than those who live farther away. This result is robust to a variety of controls and a reweighting exercise that account for potential differences between workers by location. The effect of parental proximity diminishes gradually with distance to one's parents and is driven by post-displacement wages rather than labor supply. We find some evidence that parents' job networks may help adult children to find local jobs. At older ages, living near one's parents appears to have no impact.

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1 Introduction

The typical American lives very close to their parents. In the Panel Study of Income Dynamics (PSID), about a third of household heads aged 25 to 55 live in the same neighborhood as their parents.[1,2] Economists typically explain this close proximity to parents by referencing the amenity value of being close to home. Kennan and Walker (2011), for example, describe young men's utility gain from living in the state where they grew up as equivalent to a $20,000 wage increase per year.[3] This is a substantial amount, and it could include many things.

One amenity might be the role that parents play in the labor market outcomes of their adult children. Several analyses in developing countries (e.g. Munshi and Rosenzweig, 2016), and numerous ethnographic studies in the United States (e.g. Wilson, 1987), have found that insurance through one's parents, and wider kin networks, support workers' careers. In other developed countries, Corak and Piraino (2011) and Kramarz and Skans (2014) have showed how parents can use their professional networks to help ease children's entry into the workforce.[4] Focusing on responses to adverse shocks, Kaplan (2012) provides some basic empirical evidence about earnings after job losses in the US. He develops a theoretical model where moving in with parents (coresidence) can insure workers against labor market risk.

In this paper, we investigate whether proximity to one's parents improves people's earnings after a job displacement. We find evidence that is consistent with parental resources being important. Young adults who live in the same neighborhoods as their parents at the time of displacement earn roughly the same amount as a control group five years after the displacement. Those living farther from their parents experience a large, permanent decline

[1] We use Census tracts as a measure of neighborhoods. For more details see the Census' definition at `https://www.census.gov/geo/reference/gtc/gtc_ct.html`. There are about 75,000 Census tracts in the United States with an optimum size of around 4,000 people. For a list of Census tracts by state see `http://www2.census.gov/geo/maps/trt1990/`. Molloy, Smith and Wozniak (2011) and Kaplan and Schulhofer-Wohl (2013) provide a more extensive analyses of recent trends in migration, including declining inter-state migration at different geographies.

[2] Other data sources find similar patterns. For example, Compton and Pollak (2015) use the National Survey of Families and Households to find that most Americans live within 25 miles of their mothers, and Bui and Miller (2015) use the Health and Retirement Survey to show that the median American adult lives 18 miles from their mother.

[3] Other migration models with many locations (Bishop, 2008; Gemici, 2011; Coate, 2017) find similar magnitudes using different US datasets and definitions of home location.

[4] There is some debate about how referral networks, more broadly, affect workers' wages. For example, Dustmann et al. (2017) find that hires from with employment networks raise wages, while Bentolila, Micehacci and Suarez (2010) suggest that networks may reduce wages because they might assign individuals to jobs in which they do not have comparative advantage. Alesina et al. (2015) find that "individuals who inherit stronger family ties are less mobile, have lower wages and higher unemployment…"

in earnings. We see no earnings differences for older adults who live closer to their parents.[5]

We investigate potential explanations, using a variety of approaches. Our primary empirical specification is an event study design similar to those used in the displacement literature since Jacobson, LaLonde and Sullivan (1993). Our comparison of workers displaced while near or far from parents is conceptually similar to Davis and von Wachter (2011)'s comparison of earnings outcomes of workers displaced in expansions or recessions.[6] This specification includes individual fixed effects to account for time-invariant (unobservable) differences between workers, such as motivation or ability, and year effects to control for aggregate labor market conditions.

To examine if the results are driven by other explanations, like the quality of the jobs that people lost, we use a propensity score reweighting strategy to account for observable differences between the various groups. Our primary regression results are qualitatively unchanged when we use the propensity score reweighting, which suggests that the earnings results are not driven by other characteristics of workers who live near their parents.[7] We expect that any unobservable time-varying heterogeneity would favor workers who live farther from their parents, since they should be selected on being able to adapt to new circumstances. If the unobservable differences go in the way we expect, then they would work against the recovery patterns that we observe.

We present some suggestive evidence about mechanisms that may explain our results. These include parental networks, differences in psychological resilience after a displacement (due to parental support), and in kind transfers from parents, as in Kaplan (2012)

One important feature that all of these mechanisms must explain is that lower future wage rates, and not labor supply, drive the larger earnings declines among those living farther away from their parents. We also find gradations in the effect of proximity to parents; displaced workers living in the same commuting zone as their parents, but not the same neighborhood, appear to have stronger earnings recoveries than those living farther away, but not as strong as those in the same neighborhood.[8]

[5]The discrepancy between the results for the young and the old likely reflect a change in the direction of resource flows, since older adults often live close to their parents in order to care for them in their old age. For example, Chari et al. (2015) use the American Time Use Survey to estimate the opportunity cost of informal elder care in the US at $522 billion annually. Lin and Wu (2010) find that among individuals 65 and older who had difficulties with instrumental activities of daily living, about 35% report that a child is a source of informal support. See Glaser and Tomassini (2000) for evidence outside of the US and Lin and Rogerson (1995) for a more general discussion about the "determinants of the distance between elderly parents and their adult children."

[6]For a discussion about the appropriate control group for displaced workers, see Krolikowski (2017).

[7] In an appendix, we include additional interactions of pre-displacement income with displacement dummies and find similar effects.

[8]Tolbert and Sizer (1996) provide an overview of the design of commuting zones, which are meant to

The most promising mechanism seems to be access to parental employment networks, though our analysis is limited by the relatively small sample sizes of the PSID. We find that parental proximity is associated with an increased likelihood of being employed in the industry of one's parents. We do not find any evidence for direct parental influence on job search activity or the quality of the post-displacement match as measured by tenure on the new job or the probability of switching industry or occupation.

In kind transfers from parents are another promising channel that we hope to investigate, but there is some evidence that they are not the only factor that matters. Most displaced workers in our sample, whatever their initial proximity to parents, do not return to coreside with their parents after a displacement, at least according to the PSID's contact information. We suspect that later drafts of this paper will have more to say about these transfers, however.

Our findings show the extended family's influence on migration and other labor market outcomes, like the effects of displacement on earnings. In particular, they can explain why people appear so reluctant to move from declining areas (e.g. Ganong and Shoag, 2012) and why migration responses have been smaller than expected after several local shocks (Bound and Holzer, 2000; Yagan, 2016). They also provide a micro foundation for why migration appears to be counter-cyclical (Saks and Wozniak, 2011).

Public programs designed to help after job displacements, and to stimulate declining areas, could be improved if we had a better understanding of family support after job displacements. For example, government programs might be able to economize in cases where family resources substitute for formal insurance, or replicate this support in cases where governments want to encourage geographic mobility.

The rest of this paper proceeds as follows. Section 2 describes our dataset and the construction of our regression sample. It also shows, using simple averages, that workers living near their parents have better earnings recoveries after displacements than those living farther away. Section 3 estimates an econometric model showing that this difference persists for young workers after adding regression controls. Section 4 shows these results are robust to reweighting or interaction methods that account for the sample differences between those displaced near or far from parents. Section 5 investigates possible mechanisms related to

capture the places where people both live and work. The 722 commuting zones in the continental U.S. (741 including Alaska and Hawaii) are similar in design to Metropolitan Statistical Areas but also cover areas that do not contain a central city and are designed using a algorithm that eliminates local discretion. In our context the coverage of the entire U.S. is advantageous, as is the consistent definition of geography across time (we use commuting zones defined by 1990 commuting patterns). Defining geographies based upon movements should help insure that someone who is listed as "close" to a parent is within a distance that a worker would be willing to routinely travel.

parental employment networks and differing job search activities. Section 6 provides policy suggestions and avenues for continuing research.

2 Analysis Data and Sample Averages

2.1 Dataset and Sample Construction

In choosing the appropriate data set for our analysis, we are confined by three major restrictions: 1) The data need to include inter-generational linkages ; 2) the data need to identify worker displacement events; and 3) the data need to provide (preferably many) repeated observation on individuals. To our knowledge, the PSID is one of few datasets that meets all three requirements.[9] The PSID began in 1968 with an interview of approximately 5,000 families, and follows any new families formed from the original group. We use the 1968 to 2013 waves of the PSID and include observations on individuals between the ages of 18 and 62, restricting our attention to what the PSID refers to as "household heads."[10]

Due to the genealogical nature of the PSID we have the location of adult children and their parents in each wave. At the time of the survey, the PSID also collects information about an individual's labor market experience, including their earnings during the previous calendar year. Furthermore, job displacements are determined from a question that asks respondents who have not been at their present employer for a long time: "What happened to that employer (job)?" (the individual's previous job). The two categories of responses used to identify displacements are "plant closed/employer moved" and "laid off/fired." As is standard in the displaced worker literature, we also impose that workers had at least two years with their employer and were working full-time before the displacement event so that our workers have a strong connection to the labor market.

The data set used for analysis is constructed in the following way. For a given age (the "base age") we include heads that were displaced between the date of their last survey and their current survey and heads that were not displaced. This is the "treatment" and

[9] Kaplan (2012) uses the National Longitudinal Survey of Youth 1997, which also meets these requirements. However, the intergenerational aspect of the PSID is much stronger, as the PSID collects complete and separate respondent observations for parent and child generation at any time they live in separate households over the entire panel.

[10] This is defined the person who is at least 16 years old with the most financial responsibility for the family unit. The PSID virtually always defines this as the male in a husband-wife pair or an unmarried couple who has been co-residing for at least one year. In ongoing work, we add wives of PSID household heads to the analysis sample. This allows us to include spouses of PSID individuals as well as extending panel data for female respondents in the PSID who may appear as a single head of household in some waves and the wife in a married couple in other waves.

"control" group for this base age. We include heads who were and were not living in the same neighborhood as their parents at the time of the previous interview. We repeat this procedure for every base age between 25 and 55 and stack all the samples to create the final data set.[11] To track when workers are displaced or not, let the *relative year* be zero in the base age, one in the year after, etc. For example, for the base age 40, the relative year is -8 when individuals are 32, zero when individuals are 40, and 6 when individuals are 46.[12]

Table 1 shows the summary statistics for the final sample, where we restrict to observations with non-missing parents' location information.[13] The data set consists of around 35,000 records, with an average of 20 years of observations for each, yielding roughly 700,000 person-year observations. The final data set contains about 1,350 displacement events, of which approximately 450 took place while an individual resided in their parents' neighborhood and approximately 900 occurred while an individual was not in their parents' neighborhood. Displaced workers are slightly younger, less educated, and have been with their employer for a shorter period of time in relative year -1 than their non-displaced counterparts. They also earn significantly less. Those who live outside of their parents' neighborhoods tend to be younger, more educated, and earn significantly more than those who live in their parents' neighborhoods. Strikingly, around 30 percent of adults live in the same neighborhood as their parents. We analyze the data separately for younger workers (ages 25 to 35) and older workers (ages 36 to 55); Table 1 presents summary statistics separately for this younger group of workers as well.

2.2 Some Preliminary Evidence

Figure 1 plots the average earnings before and after displacements. The top panel in Figure 1 presents the average earnings of workers who were displaced (dashed) and not displaced (solid) averaged over the base ages 25 to 35. All earnings are measured in 2007 dollars. These lines highlight the dramatic earnings consequences of worker displacement. The fig-

[11] Note that individuals may appear more than once in the final data set because they may be in the control group several times, or in the treatment group at one base age, but in the control group at another base age, etc. We use earnings information from ages 18 to 62, but displacement events only from ages 25 to 55 to avoid capturing individuals too early in their career and too close to retirement.

[12] Due to the survey design of the PSID, the location of household heads is only observed if they have previously moved out of their parents' house. Therefore, adult children who have never moved out of their parents' home are outside the scope of our analysis. The United States Census Bureau (2015, Table AD-1) reports that 50 to 60 percent of 18 to 24 year olds live with their parents (including college students living in dorms during the academic year), but only 10 to 20 percent of 25 to 34 year olds do. Thus, beginning our analysis at age 25 significantly mitigates this sample selection issue.

[13] The most common reason we have missing parents' location is that the parents are deceased.

ure delivers three messages, which have been documented in many prior studies.[14] First, displacement leads to a large initial drop in annual earnings of around \$10,000, which is around 20 to 25 percent of pre-displacement earnings.[15] Second, while earnings for these displaced individuals recover, this recovery does not exceed the earnings gains experienced by the control group of non-displaced workers. As a result, although around six years after the displacement event, earnings have recovered to their pre-displacement levels, even 10 years after the displacement event the earnings of displaced workers have not caught up with the earnings of non-displaced workers. Finally, although there is a difference in the level of earnings between the average earnings of those in the control group, which we will address in the more thorough empirical exercises that follow, there do not appear to be significant differences in the trends of earnings prior to the displacement event.

The bottom panel of Figure 1 decomposes the average earnings into those that were in their parents' neighborhood in the previous year (light gray), and those that were not in their parents' neighborhood (dark gray).[16] Many people in our sample aged 25 to 35 are not in their parents' neighborhood, so the average earnings of those individuals (displaced or not) is close to the average earnings presented in the top panel of the figure. Before describing the effects of displacement for these two groups, it is worth pointing out that individuals that live in their parents' neighborhood have significantly lower earnings than people who live farther from their parents, even before the displacement event.

The figure shows that displaced individuals that were not in the same neighborhood as their parents see large earnings losses relative to a group of individuals that were not displaced and not in the same neighborhood. This gap persists over the next 10 years. In stark contrast, those individuals that were in the same neighborhood as their parents in the year prior to the displacement event, see a much healthier earnings' recovery. Prior to the

[14]Earlier literature reviews include Hamermesh (1989), Fallick (1996), and Kletzer (1998). Recent work includes von Wachter, Song and Manchester (2009) and Davis and von Wachter (2011).

[15]One minor point about Figure 1. The earnings question refers to the earnings during the last calendar year. The displacements have been coded to have happened between the previous survey date and the current survey date. Since most PSID interviews happen in April and May, most of our displacements are referring to displacements that happen at the end of the previous calendar year. As such, the earnings on-impact, although they fall, may not reflect the entirety of the displacement event as the earnings from the last calendar year were largely unaffected by the displacement. Rather, in the year following the displacement the largest reductions may be documented. As such, in the top panel of Figure 1 the declines at year '1' are larger than at year '0'.

[16]Because of the genealogical nature of the PSID data, we typically observe the parents of single adults or of one set of parents of a married couple. We treat cases in which we have the location of the husband or wife's parents symmetrically, although sometimes this means we are using the household head's parents and sometimes parents-in-law. In some cases, we will observe multiple parents' locations (typically due to divorce of an original PSID household head); in these cases an adult child is coded as same neighborhood if they live in the same Census tract as any parent or in-law.

displacement event the difference in the earnings of the displaced and non-displaced who live in their parents' neighborhood is around \$5,000 and the earnings of the displaced individuals recover to this pre-displacement difference around six years after the displacement event. The gap in earnings between these displaced workers and the non-displaced group closes entirely within 10 years of the displacement event.

Figure 1 shows that people who live in the same neighborhood as their parents suffer small earnings losses after displacement relative to a control group of individuals who did not experience displacement.[17] In contrast, people who live farther from their parents suffer large and permanent declines in earnings. In the next two sections we verify this result with the use of more sophisticated econometric techniques.

3 Regression Results

3.1 Earnings Losses by Geographic Proximity to Parents

It is possible that systematic, observable differences, such as age or education level, exist between workers who are displaced and nondisplaced or workers who live in their parents neighborhood and those who live farther away. There may also be differences between these groups that are unobservable, such as motivation and ability. The averages presented in Figure 1 do not control for these possible differences. To address this concern, we conduct a regression analysis. This analysis allows average earnings to evolve differently for displaced and nondisplaced workers who reside close to and farther from their parents. The analysis controls for differences between these individuals that do not change over time, including observable characteristics such as gender, race, ethnicity, and education, as well as for unobservable characteristics. The econometric framework allows average earnings to vary by calendar year since, for workers, some years are better than others. The approach in this section, however, does not consider that other factors, correlated with living in the same neighborhood as ones parents, may explain the differential impact of displacement on earnings. The propensity score reweighting analysis in Section 4 addresses these additional concerns.

To be specific, we estimate the following equation:

$$e_{iat} = \alpha_{ia} + \gamma_t + X_{iat}(\beta^H + \beta^A H_{ia}) + \sum_{k=-4}^{10^+} \left(D_{it}^k \delta^k + D_{it}^k H_{ia} \zeta^k \right) + \epsilon_{iat} \qquad (1)$$

[17]The results are similar when we look at individuals who are actually co-residing with their parents as opposed to living in the same neighborhood as their parents, in the spirit of Kaplan (2012).

where e_{iat} is the annual earnings of individual i in calendar year t when the base age is a, α_{ia} represent individual-base-age dummies, γ_t control for calender-time fixed effects, X_{iat} control for an age quartic, and H_{ia} is a dummy variable indicating whether individual i was neighbors with their parents in the year prior to age a. This dummy is interacted with the age quartic in X_{iat} to allow for different age-earnings profiles for those living near their parents and farther away. This captures the apparent differences we observe in Figure 1 between the non-displaced individuals by whether they live in their parents' neighborhood or not. The variable D^k_{iat} captures whether individual i at time period t and base age a was displaced k periods ago. We pool the -4 dummy and the $+10$ dummy and omit the -2 dummy so all results are relative to two years before the displacement event. As a result, the coefficient δ^k captures the change in earnings for an individual who was displaced k periods ago and was not living in their parents's neighborhood in the previous year relative to other workers who were not neighbors with their parents but were not displaced. The coefficient ζ^k picks up the additional effect of being neighbors with your parents on the earnings outcomes of displaced workers.

Figure 2 presents the effect of displacement on earnings for workers farther away from their family, $\hat{\delta}_k$, and the effect of displacement for individuals living in the same neighborhood as their parents, $\hat{\delta}_k + \hat{\zeta}_k$, for workers aged 25 to 35. These results tell the same story as the simple averages presented in Figure 1. At the time of displacement, workers experience large declines in earnings; around \$10,000 for those living in their parents' neighborhood and around \$15,000 for those living farther away. With the average pre-displacement earnings of these groups being around \$35,000 and \$50,000, respectively, this represents a 30 percent decline in earnings at the time of displacement. The post-displacement recovery, however, is quite different for the two groups. The group living farther away from their parents experiences a small recovery in the short- to medium-run but still has earnings losses of around 30 percent even 10 years after the displacement event. In contrast, the group that was living in the same neighborhood as their parents prior to the displacement event experiences a steady recovery in the years following the displacement event, with earnings losses indistinguishable from a full recovery after six years.[18]

3.2 Employment, Hours, and Wages

The earnings outcomes in the previous section could result from a few different sources. First, those displaced while living close to their parents could experience higher employment rates

[18] The results are similar if one drops observations that have zero annual earnings or, alternatively, if one uses the log of annual earnings on the left hand side in equation (1) as opposed to the level of earnings.

after the displacement event (extensive margin). Second, those displaced while living close to their parents might not necessarily experience higher employment rates, but they could, conditional on employment, work much longer hours (intensive margin), resulting in higher earnings. Finally, even if those displaced while living in their parents' neighborhood are less likely to be employed and work shorter hours, they could experience higher earnings because of markedly higher remuneration per hour. It turns out that those who were displaced when living close to their parents work for better pay, but they have comparable working hours to those who did not live in their parents' neighborhood and they are no more likely to be employed.

Figure 3 presents the results from estimating equation (1) with three different outcomes: employment status at the time of the interview, hours worked during the last calendar year (conditional on having worked last year), and earnings per hour. The top panel shows the probability of being employed at the time of the survey. This falls dramatically during the survey after the displacement event, as many individuals have not returned to work as of that time. The graph suggests displaced individuals are around 35 percentage points (pp) less likely to be employed in the year after the displacement event than non-displaced individuals. Although individuals living in their parents' neighborhood are perhaps slightly less likely to be employed two to four years after the displacement event, the differences between these point estimates are not statistically significant. As such, the two groups seem to have similar post-displacement employment patterns.

The middle panel of Figure 3 shows the results from estimating equation (1) with the hours worked last calendar year as the outcome, where we condition on positive hours (some employment). The results suggest that there does not seem to be any systematic differences in the hours recovery for those living close to and farther away from their parents prior to the displacement event. Both groups see a drop in their hours worked of around 400 hours at the time of displacement (around 15 percent of the 2,000 hours prior to displacement), a strong recovery in the three years following the displacement event, and some signs that hours never fully recover, even 10 years after the displacement event. Although those living close to their parents appear to work a little less in the year after the displacement event and a little more 8 to 10 years after the displacement event, these differences are not statistically significant.

The bottom panel of Figure 3 shows how hourly earnings, conditional on positive hours, move around the time of displacement for those who are living in the same neighborhood as their parents and those living farther away. These results resemble the earnings results in Figure 2. Those living close to their parents have wage reductions of around \$2/hr whereas those that live outside of their parents' neighborhood experience a fall in hourly earnings of around $5/hr. Moreover, those individuals that had been living in the same neighborhood as their parents at the time of displacement see their hourly earnings recover within six years, and those individuals that lived far away from their parents see no recovery.

This analysis strongly suggests that young workers living in their parents' neighborhood prior to a job displacement experience stronger labor market recoveries than those who live farther away from their parents. We can think of three major mechanisms which would be consistent with these results. First, parents may provide informal insurance during adverse labor market shocks, stepping in with resources, such as housing, child care, and food, when their adult children experience job losses (Kaplan, 2012). Second, parents may be able to assist their adult children in finding employment after their job losses through their social networks (Kramarz and Skans, 2014). Third, parents may provide additional motivation and encouragement to their children after the job displacement, which may help with the job search process (Dalton, 2013).

Although we take up these issues in more detail in Section 5, here we note that all three of these channels should diminish with the age of the adult child and the geographic distance between the child and their parents. For example, as an adult child grows older (and their parents age) living close to one's parents may be a sign that your parents need your assistance, implying that the flow of resources begins to flow from adult child to parent. Similarly, although it may be easier to provide in-kind assistance when children are close, this gets harder as they live farther away. The following section shows that the data support these basic insights.

3.3 Earnings Results by Age and Proximity to Parents

Figure 4 shows the results of estimating equation (1), where we look at young displaced workers who are living very close to their parents (same neighborhood), close to their parents (same commuting zone, but not same neighborhood), and farther away from their parents (outside of the commuting zone).[19] This figure suggests that those living close to their parents, but not in the same neighborhood, also experience significantly better post-

[19] We augment equation (1) by including an interaction of the age quartic with an indicator for whether an individual is in the same commuting zone, but not the same tract, and for whether an individual is in the same tract as their parents. Additionally, we interact the displacement dummies with whether an individual lives in the same commuting zone as their parents and the same tract as their parents. This approach allows for mutually exclusive age quartics for the three different groups (same tract, same commuting zone but not same tract, and different commuting zone) while testing for a distinct effect of displacement for those in the same tract as opposed to just the same commuting zone as their parents.

displacement earnings outcomes than those who live farther away. In particular, during the ten years following the displacement event, those living outside of their parents' commuting zone see a continuing decline in their earnings, resulting in earnings' losses of around 30 percent in the long-run. Individuals who lived in their parents' commuting zone avoid this persistent decline, and even see a small recovery during the first few years after displacement resulting in a 20 percent earnings reduction in the long-run. Although living in the same neighborhood as one's parents has the most benefits to young adults who lose their jobs, this positive effect seems to diminish only gradually with distance to one's parents.

Figure 5 shows the results of estimating equation (1) for older workers, aged 36 to 55. As with the previous figure, the earnings losses associated with displacement are large and persistent. This figure, however, suggests that for older workers, living in the parents' neighborhood does not help post-displacement labor outcomes in the same way that it assists younger workers. We find this result intuitive as older workers are more likely living close to their parents because their parents need them, not the other way around.

4 Propensity Score Reweighting

Displacements have smaller effects on workers who live closer to their parents. People who live closer to their parents also have less formal education, have lower incomes, and are less likely to be in managerial and professional occupations. These differences may drive the effects.

To see if observable differences in jobs, or observable worker characteristics, drive the effects, we use propensity score reweighting. Essentially, we compare people with similar characteristics before the displacement. People who live closer to their parents still do better after a displacement, even after we control for these important differences. The result's robustness to controlling for the detailed characteristics available in the PSID makes it much more plausible that parents assist children who live nearby in important ways.

Unobserved differences could affect our results, but they would have to have two properties. First, they would have to be time varying around a displacement in a relevant way. Second, the numerous variables that we control for would have to be poor proxies for these unobserved differences.

4.1 Methodology and Results

The propensity score reweighting allows us to control for heterogeneous effects of a displacement related to the observable quality of the job lost, as well as observable characteristics of the worker. For example, if workers who live farther from their parents have jobs with observably better firm-specific match quality, then the reweighting would address this by emphasizing workers who were away from their parents, but had jobs with lower wages in less desirable occupations. The reweighting also incorporates individual characteristics, like educational attainment and age, that could relate to workers' psychological resilience. Differences in psychological resilience seem unlikely to lead to the effects that we find, however, since people who live farther from their parents should be selected on being able to deal with problems independently, without parental support.

In this context, reweighting is particularly attractive because it allows us to reduce the dimensionality of the problem by accounting for several observable variables at the same time.[20] For example, we can ensure that people not only make the same income before displacement, but reweighting (subject to using a somewhat flexible functional form) can model people making the same income, working in the same occupation, and having an employer in the same industry. In the next two subsections we explain the type of propensity score reweighting that we use, and show results from employing reweighting. An appendix also provides some placebo tests designed to assess the strategy's merits using the control groups.

4.1.1 Methodology

Here we calculate the means and regression coefficients as we did before in Section 3, but using weights designed so that the observable characteristics of all workers match those of workers who were displaced while living close to their parents. The difference between the various groups in our plots of average (reweighted) earnings around displacement can be interpreted as an effect of the treatment on the treated, where the treatment is being close to one's parents before a job displacement. This links our analysis directly to the literature on propensity score reweighting, e.g. Rosenbaum and Rubin (1983) and Hirano, Imbens and Ridder (2003), but with the slight complication that we examine multiple treatment arms, as in Imbens (2000).

The reweighted regressions allow us to estimate dollar costs of displacements for different

[20] In an appendix, we include a specification that controls heterogeneous effects of displacement by baseline income using interactions with displacement dummies.

groups of people, while holding several co-variates fixed across groups. Intuitively, this should mean that these co-variates will have similar effects for each group around displacement, since they take on similar values. The exercise is similar to allowing several interaction terms in the regression specification, and for comparison we present results from such an interacted model separately in Appendix B. In Appendix C, we perform the same exercise, but using only a subset of observations where there is strong common support according to the selection method proposed by Crump et al. (2009).

We compute the weights for person i, at base age a, who is in a group defined by whether they were displaced (D or N) and whether they lived close to their parents (H or A), $j \in \{HD, AD, HN, AD\}$, using the following formula. The formula is an application of a typical reweighting scheme (e.g. DiNardo, Fortin and Lemieux, 1996; Fortin, Lemieux and Firpo, 2011) to the case of multiple treatment arms. Note that the weight is one for the treatment group ($j = HD$) since we are reweighting all other observations to have the same characteristics as this group.

$$W_{ia} = \frac{\mathrm{P}(j = HD|X)}{\mathrm{P}(j = HD)} \frac{\mathrm{P}(j)}{\mathrm{P}(j|X)} \tag{2}$$

Empirically, we estimate probabilities conditional on X using a multinomial logit regression, as suggested by Imbens (2000).[21] The unconditional probability terms in each regression are simply the proportion of the sample made up by the group, as suggested by Fortin, Lemieux and Firpo (2011).

Table 2 shows a validation of the weights using several of the covariates in X as well as some other variables that were not included in the reweighting. It reports the means, standard deviations, and p-values of a Wald test of equality with the group of people who were young and lost their jobs while living in the same census tract as their parents. In keeping with our regression analysis it includes each person separately for each year they were in the sample of people at risk for a displacement. Panel A shows these statistics using the initial PSID person weights and Panel B uses the propensity score reweights. As intended, the differences across samples in Panel A disappear. In Panel B, each group has similar initial earnings, ages, years of education, and a similar likelihood of having children.

[21] The predictors in the multinomial logit regression are a quadratic term and level changes in income, the level of wages, a college dummy and a linear term for the number of years of completed education, dummies for one digit occupations, a linear term for job tenure, a linear term in age, a dummy for gender, and a dummy for being black. The regression is un-weighted and all of the controls are the average values of the variables in the three years leading up to the event (ignoring years where they are not observed).

4.1.2 Earnings Results using Propensity Score Reweighting

We begin by showing the effects of reweighting in terms of the simple means that we began with in Section 2.2. Figure 6 shows means of earnings around displacement for people living in the same tract as their parents and reweighted means for people farther way. We see that the experiences of both groups are (not surprisingly) similar before displacement, as well as shortly after, but that people who were closer to their parents do better later on. The two earnings plots are very similar before displacement, and they actually track each other quite well in terms of the initial drop in earnings. After a few years, however, the earnings of those who were closer to their parents begin to out-pace the earnings of people who were farther away. In the final years this difference is large, around seven thousand dollars, and statistically significant at the five percent level. This increasing difference in favor of those who were closer to home is the opposite of the pattern for the control groups, where people who lived farther from their parents tended to do better later on.

Figure 7 shows the baseline regression specification (Equation 1), but with the new weights.[22] It confirms that the inverse probability reweighting procedure provides similar qualitative results to the main specification. As before, there are substantial drops in earnings following a displacement, though the initial losses are both about $10 thousand. Earnings trajectories are similar, again, until about five years out, when they begin to diverge. People living closer to their parents see no detectable earnings losses in years six through ten, with positive point estimates. People who live farther away from their parents do have detectable earnings losses ten or more years after the displacement. These losses are more modest than the baseline regressions, but thy are still substantial, about eight thousand dollars, or 15 percent of initial earnings.

The robustness exercises lend credence to the idea that parents play a causal role after job displacement. After controlling for several relevant variables, we find that our baseline results are qualitatively unchanged. The similarity across the many specifications suggests that we have not omitted variables that are important for the recovery process and that the effect of being displaced is similar across people with these different observable characteristics.

[22] We continue to use clustered standard errors, which address heteroskedasticity induced by the weighting, along with mechanical correlations across observations. Goldschmidt and Schmieder (2015) also use a similar approach in a relatively similar context, making many of the same choices. The main difference with their approach is we use reweighting, while they rely on nearest neighbor matching.

5 Investigating Mechanisms

5.1 Search Intensity

This section outlines some results about how search intensity for young individuals varies with proximity to parents. Although our analysis does not show any statistically significant relationship between the search intensity of young adults and living in the same neighborhood as one's parents, it also does not decisively rule out a small, positive relationship between the two. Taken as a whole, however, our results suggest that the marked differences we see in post-displacement earnings trajectories between those close to their parents and those farther away are likely not explained by differing post-displacement search activities by these two groups.

The search activities data we use here only started in 1988 (as opposed to 1968 for the main analysis) and we stop the analysis in 2013, yielding 18 years of data. This means that the sample used for this exercise will be different from the one in the main text. Nonetheless, unless we think that the relationship between search intensity and parental proximity has changed from the 70s and 80s to time thereafter, the present analysis should be representative of the entire period. Other than that, we use the same "stacked" version of the data in this analysis as described in Section 2. The search activity questions ask about what methods of job search were used by respondents, e.g. checked with private employment agency, checked with friends or relatives, and placed or answered ads.

Table 3 presents summary statistics on search intensity for those living in the same tract as their parents and for those living farther away, by labor force status at the time of the interview, for younger (25-35) and older (36-55) adult children. The last two columns of this table suggest that young individuals living close to their parents are more likely to engage in some form of job activity than those living farther away; this applies to those who are unemployed but not those who are employed at the time of the survey.[23] This difference between individuals close to and far away from their parents, for individuals who are not working, is driven both by search activities that do not include friends and relatives, and search activities that do include friends or relatives.

The bottom panel of the table shows that older workers are, on average, less likely to be

[23]The pooled columns present results when unemployed and employed individuals are both used in the estimating equation. A comparison between those two columns should be informed by the fact that those living close to their parents are more likely to be unemployed and unemployed individuals are more likely to search. The latter can be seen in Table 3 by comparing the search activities of the employed and the unemployed. On the former, the unemployment rate of those living close to their parents is far higher than for those living farther away.

searching for a new job than young workers, regardless of labor force status. The patterns of search activities by proximity to parents for older adults are similar to younger workers, although the differences between the searching behavior of those close to their parents and farther away is more similar than for younger workers. In particular, older workers workers who are unemployed at the time of the survey are no more likely to check with their friends or relatives during the search activity than those who live farther away.

In order to go beyond these basic comparisons of means, we estimate the following linear probability model:

$$search_{it} = \alpha + \beta Sametract_{it} + \gamma X_{it} + \epsilon_{it}$$

where $search_{it}$ is a dummy for whether individual i reported any job search activity in period t, $Sametracts_{it}$ is a dummy for whether individual i is living in their parents' tract time period t, and X_{it} includes a host of controls.

Table 4 presents the results of this analysis, by labor force status and pooled results. The first column reproduces the average difference in the probability of searching for a job between unemployed young adults living in the same neighbrohhod as their parents and those living farther away from Table 3. Columns (2) and (3) add increasing number of controls, including demographic controls, such as age, race, and education, and year fixed effects. These results rule out large effects of parental proximity on young adult search activity but suggest a small, positive relationship (during unemployment) between the two that is not statistically significant. Column (3), for example, suggests that living in the same neighborhood as one's parents increases the probability of unemployed young adults engaging in search activities by 4.2 pp. Column (4) shows that employed young adults who live in their parents' neighborhood, conditional on the controls in column (3), are slightly less likely to be engaged in search activities than young adults living away from home, but the point estimate is virtually zero and precisely estimated.

Column (5) pools employed and unemployed young adults and includes individuals fixed effects and a control for unemployment status at the time of the interview in addition to the other controls in columns (3) and (4). This approach uses variation in proximity to parents within an individual's observations to identify the effect of parental proximity on search activity as opposed to variation in proximity to parents across individuals. Despite this difference in methodologies, the results of column (5) support the results by labor force status in columns (3) and (4): Young adults living close to their parents are slightly more likely to engage in search activities than young adults living farther away, but the positive coefficient is not statistically significant.

Taking these results at face value, we conclude that the markedly differential earnings trajectories we observe post-displacement for young adults living close to and farther away from home are likely not explained by variations in search intensity among the two groups, but a more definitive statement would warrant further research with different data. Moreover, our analysis thus far does not speak to the effectiveness of job search, a topic to which we now turn.

5.2 Job Networks and Match Quality

Young adults living close to their parents may have more productive job search experiences and healthier earnings as a result of family networks, much like in Kramarz and Skans (2014). The basic idea is that, after job loss, parents may be able to assist their adult children by tapping into their own employment networks to help their adult children to a) gain employment faster; b) gain employment in their own industry/occupation; and c) facilitate better match quality on post-displacement jobs. We can test these hypotheses using PSID data and this section pursues evidence for these three testable predictions.

5.2.1 Unemployment Duration

[To be completed – unemployment duration does not seem to vary much by proximity to parents]

5.2.2 Employment in Parents' Industry

Table 5 presents some summary statistics on the probability of individuals' working in their parents' industries.[24] For this table we consider adult children to be close to their parents if they live in the same commuting zone as their parents.[25] On average, young individuals living in the same commuting zone as their parents are more likely to be working in their parents' industry; this correlation is predominantly driven by employed young adults. The last two columns of Panel B suggest that older workers who live in their parents' commuting zone are also more likely to be employed in their parents' industry, but this is driven by employed workers; unemployed older adults who live in their parents' commuting zone are

[24] This is an indicator of whether either of the parents of the individual (or the parents of the individual's partner) are employed in the same industry as the individual.

[25] It is not clear a-priori at what level of geography networks may operate in, however, we think that a local labor market is perhaps the most relevant. Also, we choose the commuting zone as the broader geographic region because of our results in Section 3.3, where we find that those living in the same commuting zone tend to fair better than those who live farther away, but not as well as those who live in the same tract as their parents. In the regression results that follow we allow for different levels of geography.

less likely to be employed in their parents' industry. Comparing the two panels reveals that younger adults are more likely to be working in their parents' industry than older adults.

To estimate these correlations holding observables constant, we estimate a similar specification as in Section 5.1, but use as the outcome an indicator of whether the young adult child is employed in the same industry as their parent:

$$Same\_industry_{it} = \alpha + \beta_1 Sameczone_{it} + \beta_2 Sametract_{it} + \gamma X_{it} + \epsilon_{it}$$

We include a dummy for both whether the individual shares a commuting zone with their parents and (in most specifications) whether they additionally share a tract with their parent.

Table 6 presents the results of this analysis, where we have pooled the unemployed and employed, by worker age and proximity to parents. The first column reproduces the average difference in the probability of searching for a job between young adults living in their parents' commuting zone and those living farther away that we documented in Table 5. The regression shows that this positive effect of parental proximity on being in the same industry as one's parents is statistically significant. Column (2) shows that after conditioning on living in the same commuting zone, living in the same neighborhood as one's parents has no additional impact on being in the same industry as one's parents. Columns (3) and (4) add increasing number of controls, including demographic controls, such as age, race, and education, year fixed effects, and individual fixed effects. In the specification that controls for time invariant worker characteristics, the coefficient on living in the same commuting zone as one's parents is positive and statistically significant. The point estimate suggests that living close to one's parents raises the probability of being employed in their industry by 3.8 pp. The average probability in the sample of being in the industry of one's parents is around 19 percent. Hence this coefficient represents a sizable increase in the propensity to be employed the industry of one's parents.

Column (5) of Table 6 shows the same specification estimated using older workers, aged 36 to 55. The effect also seems present for older workers, which we are still digesting. Column (6) estimates the same equation as in column (4) but uses an indicator for being in the same state (as opposed to the same commuting zone) as one's parents to measure parental proximity. The coefficient on this measure of geographic proximity turns out to be insignificant, although similar in magnitude to the coefficient on the same commuting zone in column (4). These placebo tests are consistent with our earnings findings which uncovered a stronger earnings recovery after displacement for young adults living close to their parents, but not for older workers or younger workers living in the same state as their parents.

These results suggest that individuals living in the same neighborhood as their parents are more likely to be employed in their parents' industry, after controlling for observables. We take this as suggestive evidence that employment networks accessed via parents may be responsible for the differing earnings trajectories after displacement experience by young adults who live in their parents' commuting zone compared to those who live farther away.

5.2.3 Quality of the Job Match

[Industry/Occupation switching: To be completed.]

[Tenure on post-displacement job: To be completed.]

6 Conclusion

Young adults who live closer to their parents experience smaller earnings declines after job displacements. We find evidence that assistance from parents drive these differences, as they are not explained by observable differences between people who live different distances from their parents. The result suggests that family ties are an important part of workers' economic geography.

If being close to one's parents is particularly valuable after a job loss, then people may be more reluctant to relocate for new jobs. People's reluctance to move could, in turn, make local recessions longer and more pronounced. This would also help to explain why workers appear to be less mobile in economic downturns (Saks and Wozniak, 2011) and why immigrants appear to be more mobile than natives (Cadena and Kovak, 2016). More directly, parental resources may be an important part of the findings of researchers like Kennan and Walker (2011) and Coate (2017) that workers place a large premium on living close to their places of birth.

These findings can inform how local governments structure assistance programs after job losses. If governments would like workers to re-allocate themselves after job losses, then they might wish to establish programs that substitute for having parents nearby. Even if these programs perfectly crowd out parental investments, they may still be worthwhile since they would facilitate workers re-allocating themselves.

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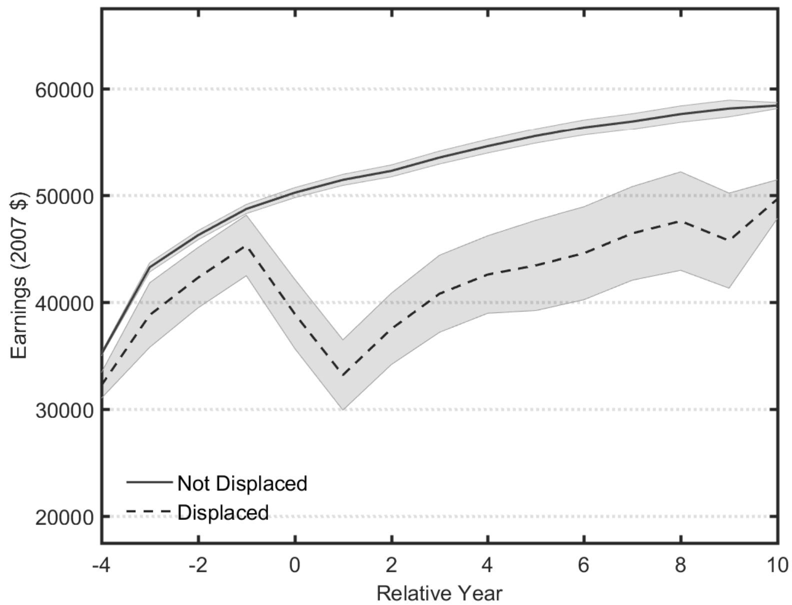
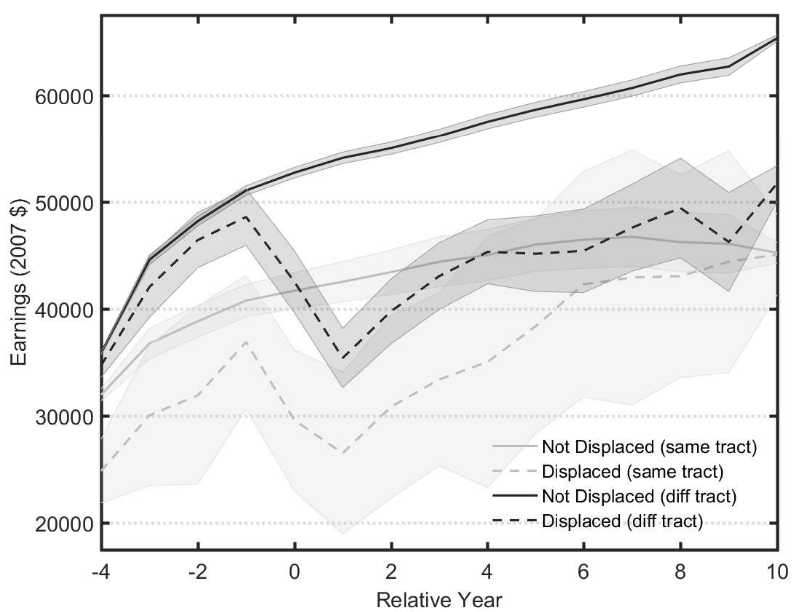


(a) Average Earnings for Young Displaced and Non-Displaced Workers



(b) Average Earnings for Those In Their Parents' Neighborhood and Not

Figure 1: Average Earnings for Young Displaced Workers by Proximity to Parents

Source: Panel Study of Income Dynamics; author's calculations. Shaded areas represent 95% confidence intervals.
Note: Young workers (aged 25 to 35) who live in the parents' neighborhood experience much stronger earnings recoveries after a displacement event than young workers who are not living in their parents' neighborhood.

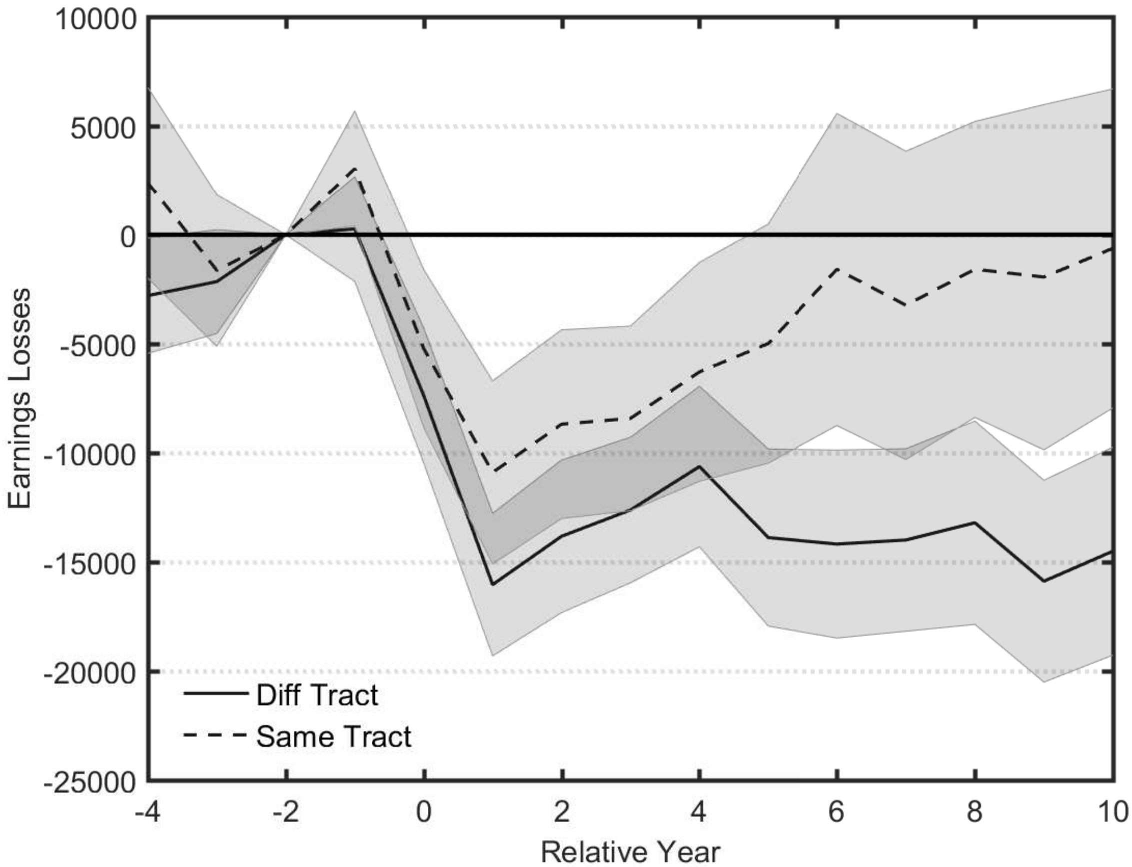
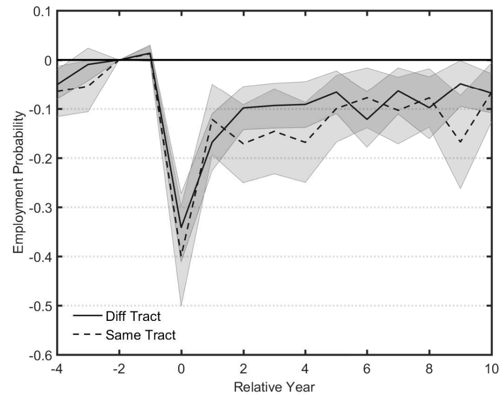
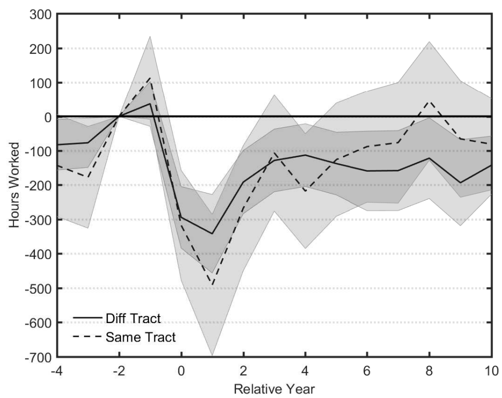


Figure 2: Earnings Losses for Young Displaced Workers

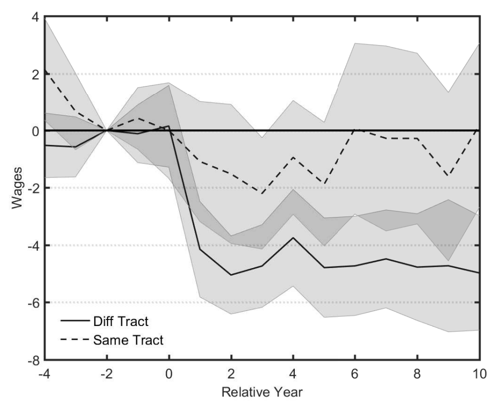
Source: Panel Study of Income Dynamics; author's calculations using equation (1). Shaded areas represent 95% confidence intervals where standard errors are clustered at the individual level.
Note: The regression analysis supports the basic intuition in Figure 1: In the medium- and long-run, young workers living in the same neighborhood with their parents experience a full recovery in earnings after a displacement event. Young workers not living in their parents' neighborhood experience large and permanent earnings losses, amounting to around 30 percent of their pre-displacement earnings even 10 years after the displacement event.



(a) Employment Status



(b) Hours Worked



(c) Hourly Earnings

Figure 3: Employment, Hours, and Wages for Young Displaced Workers

Source: Panel Study of Income Dynamics; author's calculations using equation (1). Shaded areas represent 95% confidence intervals where standard errors are clustered at the individual level.

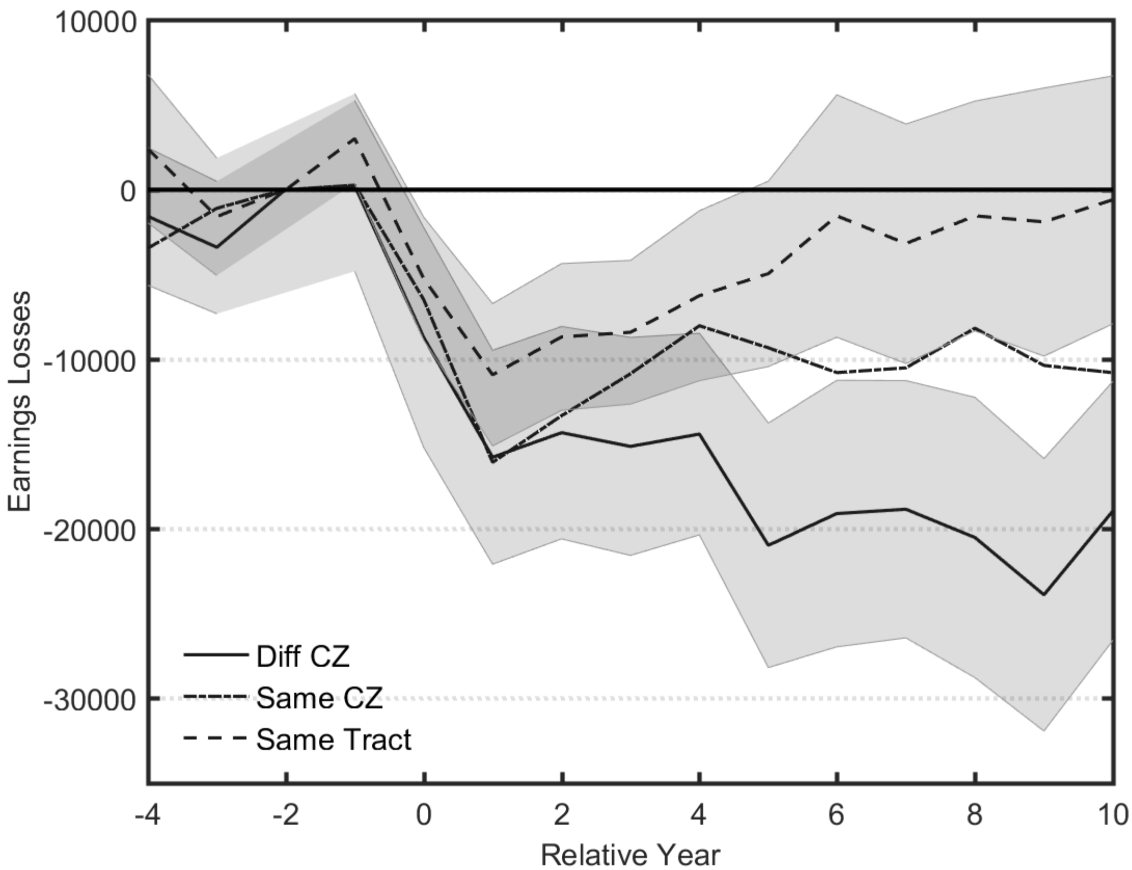


Figure 4: Earnings Losses Young Workers by Proximity to Parents

Source: Panel Study of Income Dynamics; author's calculations using equation (1). Shaded areas represent 95% confidence intervals where standard errors are clustered at the individual level.
Note: Those individuals living close to their parents (in the same commuting zone), but not in the same neighborhood, also experience significantly better post-displacement earnings outcomes than those who live farther away. The interactions between the displacement dummies and the same commuting zone dummy are different from zero at the 95 percent confidence level five, eight, and nine years after displacement. The interactions between the displacement dummies and the same tract dummy are statistically different from the same commuting zone interactions six and ten years after the displacement event.

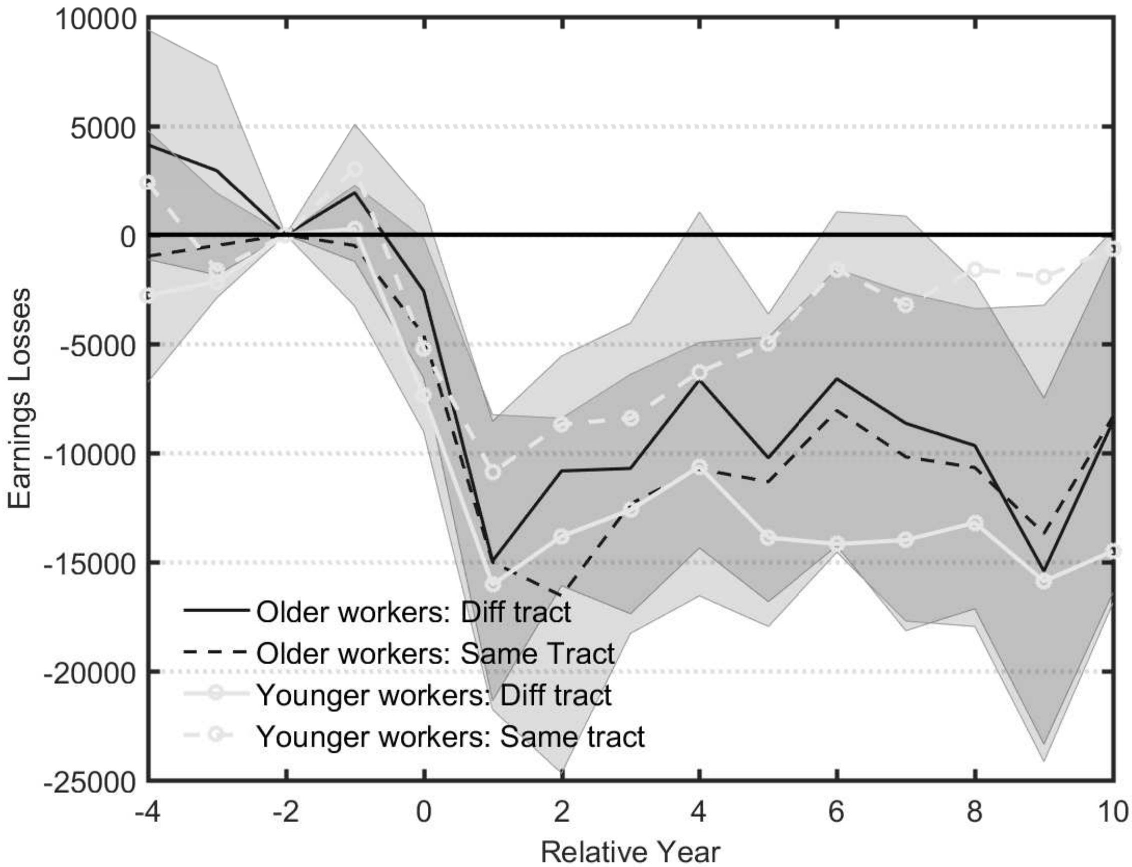


Figure 5: Earnings Losses for Older Displaced Workers

Source: Panel Study of Income Dynamics; author's calculations using equation (1). Shaded areas represent 95% confidence intervals where standard errors are clustered at the individual level.
Note: Older workers (aged 36 to 55) who live in their parents' neighborhood experience similar earnings losses to workers who live farther away.

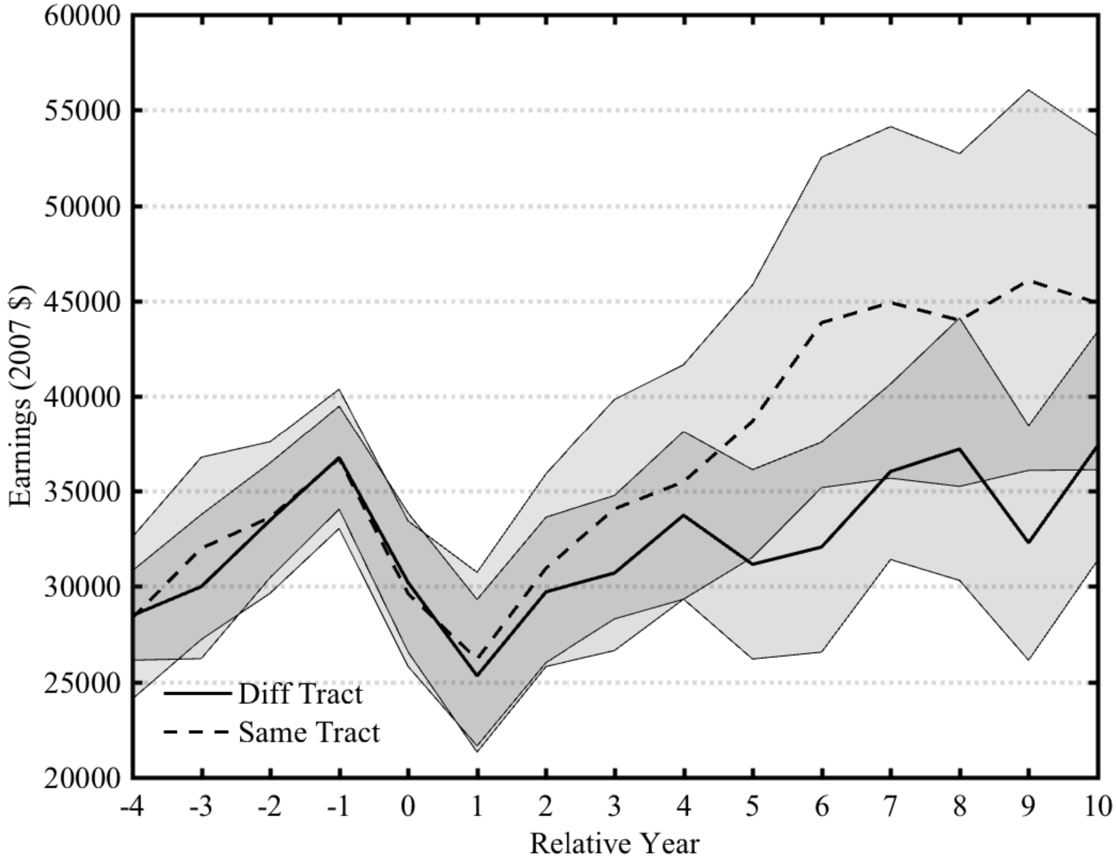


Figure 6: Means After Reweighting

NOTES: Plotted are mean earnings in years surrounding a displacement event, using weights based on propensity scores. The dashed lines are the effect for people who lose their jobs while they live in the same census tract as a parent (in the PSID sample). Solid lines are for people who live in different tracts. Shading represents 95 percent confidence intervals around the solid lines using standard errors clustered by the person in the sample.

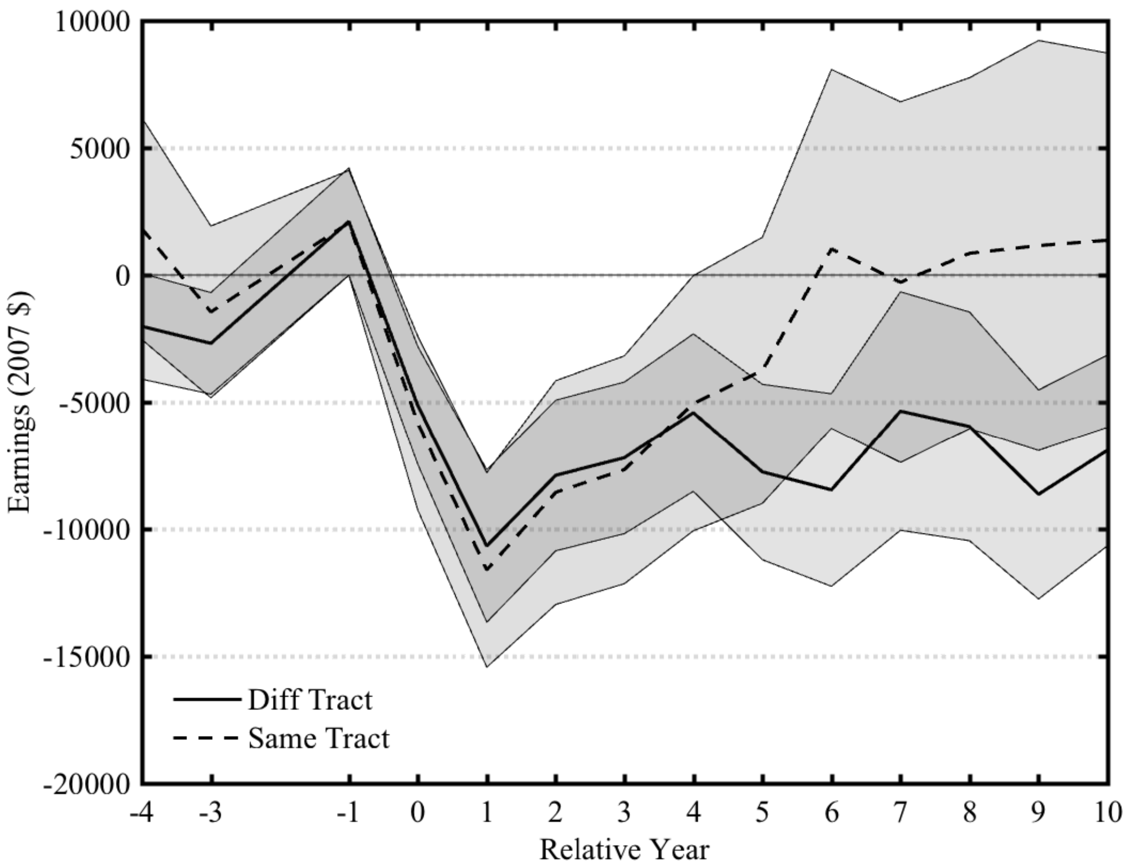


Figure 7: Regressions with Propensity Score Reweighting

NOTES: Each plot is a (combination of) regression coefficient[s] from a pooled panel regression of income on real earnings (in 2007 dollars), using weights based on propensity scores. The dashed lines are the effect for people who lose their jobs while they live in the same census tract as a parent (in the PSID sample). Solid lines are for people who live in different tracts. Shading represents 95 percent confidence intervals around the solid lines using standard errors clustered by the person in the sample.

Variable	Not Displaced	Displaced	Not Displaced (T)	Displaced (T)	Not Displaced (A)	Displaced (A)
	A. All Workers Aged 25 to 55					
Earnings	52,322	45,914	46,037	39,664	54,768	48,902
Age	33.2	31.7	34.7	32.5	32.6	31.3
Years of Schooling	13.5	12.9	12.7	12.1	13.8	13.2
Employer Tenure	8.1	6.1	9.6	6.6	7.6	5.8
Fraction in Parents' Tract	0.28	0.32	1	1	0	0
Number of Children	1.12	1.11	1.20	1.20	1.08	1.07
Fraction Male	0.84	0.86	0.79	0.85	0.87	0.87
# of records	35,145	1,326	9,772	435	25,373	891
	B. Young Workers Aged 25 to 35					
Earnings	48,681	45,339	40,864	36,942	51,227	48,662
Age	29.1	28.7	29.1	28.4	29.1	28.9
Years of Schooling	13.6	12.8	12.7	12.2	13.8	13.1
Employer Tenure	6.2	5.1	6.8	5.3	6.0	5.1
Fraction in Parents' Tract	0.25	0.28	1	1	0	0
Number of Children	1.01	1.07	1.19	1.11	0.95	1.06
Fraction Male	0.84	0.85	0.79	0.82	0.86	0.87
# of records	18,972	762	4,805	229	14,167	533

Table 1: Summary Statistics

Source: Panel Study of Income Dynamics; author's calculations.
Note: Weighted averages using unbalanced data from the 1968-2013 PSID surveys. Dollar figures are in 2007 dollars using the CPI-U-X1. All variables are measured in the year before the base age (relative year -1). 'T' stands for those individuals living in their parents' tract (neighborhood) in relative year -1 and 'A' stands for those individuals away from their parents' neighborhood. The PSID sample of household heads is composed chiefly of men. We restrict to observations that have non-missing parents' location information.

	PSID weights				Re-weighted			
	Same tract		Diff tract		Same tract		Diff tract	
Variable	Displaced	Control	Displaced	Control	Displaced	Control	Displaced	Control
Income	33,977	40,060	47,740	49,822	33,977	33,482	33,386	33,633
	(1851)	(855)	(1854)	(635)	(1851)	(709)	(1409)	(541)
	1.00	0.00	0.00	0.00	1.00	0.79	0.80	0.86
Avg chg in income	2,692	2,178	2,897	3,515	2,692	2,295	3,608	2,565
	(748)	(162)	(551)	(120)	(748)	(179)	(544)	(140)
	1.00	0.50	0.83	0.27	1.00	0.61	0.32	0.87
Yrs of education	12.11	12.77	13.22	13.87	12.11	12.20	12.36	12.19
	(0.23)	(0.10)	(0.14)	(0.06)	(0.23)	(0.09)	(0.15)	(0.11)
	1.00	0.00	0.00	0.00	1.00	0.68	0.36	0.75
Avg. tenure	5.53	7.25	5.44	6.37	5.53	5.72	5.34	5.53
	(0.34)	(0.18)	(0.23)	(0.09)	(0.34)	(0.12)	(0.26)	(0.10)
	1.00	0.00	0.83	0.02	1.00	0.56	0.66	0.99
Share manager/professional	0.17	0.27	0.35	0.44	0.17	0.19	0.18	0.17
	(0.04)	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.03)	(0.01)
	1.00	0.03	0.00	0.00	1.00	0.75	0.88	0.96
Share in goods industries	0.54	0.43	0.50	0.35	0.54	0.48	0.50	0.42
	(0.05)	(0.02)	(0.04)	(0.01)	(0.05)	(0.02)	(0.04)	(0.02)
	1.00	0.04	0.51	0.00	1.00	0.26	0.56	0.03
Age	29.02	29.97	29.89	30.01	29.02	28.89	28.88	28.93
	(0.30)	(0.09)	(0.20)	(0.05)	(0.30)	(0.09)	(0.22)	(0.08)
	1.00	0.00	0.02	0.00	1.00	0.68	0.70	0.76
Share male	0.83	0.80	0.87	0.87	0.83	0.82	0.77	0.82
	(0.04)	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.05)	(0.02)
	1.00	0.52	0.41	0.32	1.00	0.82	0.36	0.93
Avg num children	1.17	1.28	1.11	1.04	1.17	1.22	1.22	1.21
	(0.13)	(0.06)	(0.09)	(0.03)	(0.13)	(0.06)	(0.11)	(0.04)
	1.00	0.41	0.70	0.33	1.00	0.74	0.80	0.81
N	161	3363	336	8757	161	3363	336	8757

Table 2: Means of reweighted and initial sample

NOTES: This reports means for each group in the initial sample using PSID weights in the first four columns and the propensity score reweights in the last four columns. For each variable, we report the mean, the standard error f that mean, and a p-value of a Wald test that this mean is the same as the value in the first column. Standard errors and p-values adjust for clustering at the individual level.

	Unemployed (A)	Unemployed (H)	Working (A)	Working (H)	Pooled (A)	Pooled (H)
Panel A: Young Workers						
$\mathbb{P}[\textit{any search activity}]$	0.78	0.83	0.070	0.065	0.079	0.091
$\mathbb{P}[\textit{checked w/ frnds or rels}]$	0.25	0.34	0.023	0.016	0.028	0.029
$\mathbb{P}[\textit{searched but not w/ frnds or rels}]$	0.62	0.73	0.063	0.059	0.071	0.084
Panel B: Older Workers						
$\mathbb{P}[\textit{any search activity}]$	0.67	0.75	0.050	0.037	0.060	0.066
$\mathbb{P}[\textit{checked w/ frnds or rels}]$	0.26	0.27	0.016	0.014	0.022	0.026
$\mathbb{P}[\textit{searched but not w/ frnds or rels}]$	0.57	0.64	0.044	0.032	0.053	0.059

Table 3: Summary Statistics of Search Intensity by Proximity to Parents and Labor Force Status

Source: Panel Study of Income Dynamics 1988-2013
Note: Young workers living in the same neighborhood as their parents are more likely to engage in search activities than young workers living farther away (pooled results). A similar patterns holds for older workers although it is less pronounced. Parenthetical (A) stands for "away," i.e. those not in the same neighborhood as their parents at the time of the survey, and (H) stands for "home," i.e. those living farther away.

	(1)	(2)	(3)	(4)	(5)
	Unemployed	Unemployed	Unemployed	Working	Pooled
Same tract	0.047	0.039	0.042	-0.007	0.0097
	(0.049)	(0.044)	(0.043)	(0.009)	(0.013)
Unemployment					0.67***
					(0.034)
Observations	1,996	1,718	1,718	63,253	64,971
R-squared	0.003	0.21	0.27	0.02	0.14
Demographic controls	NO	YES	YES	YES	YES
Year FEs	NO	NO	YES	YES	YES
Individual FEs	NO	NO	NO	NO	YES
Number of individuals	413	369	369	2,209	2,235

Clustered standard errors in parentheses

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

Source: Panel Study of Income Dynamics

Table 4: Any Job Search Activity for Young Workers

Source: Panel Study of Income Dynamics 1988-2013
Note: Young workers (25 to 35 year olds) living in the same neighborhood as their parents are no more likely to engage in search activities than young workers who live farther away. This does not depend on employment status. Industry and occupation fixed effects are at the one-digit level.

	Unemployed (A)	Unemployed (H)	Working (A)	Working (H)	Pooled (A)	Pooled (H)
Panel A: Young Workers						
$\mathbb{P}[in\ parent's\ industry]$	0.16	0.18	0.16	0.21	0.16	0.21
Panel B: Older Workers						
$\mathbb{P}[in\ parent's\ industry]$	0.061	0.040	0.056	0.070	0.056	0.069

Table 5: Summary Statistics of Sharing Parent's Industry by Parental Proximity and Labor Force Status

Source: Panel Study of Income Dynamics 1968-2013
Note: For unemployed workers, their recorded industry is the industry of their previous job. Results are based on large sectors but looking at finer levels of disaggregation does not alter the conclusions. Paranethetical (A) stands for "away," i.e. those not in the same commuting zone as their parents at the time of the survey, and (H) stands for "home," i.e. those living farther away.

	(1)	(2)	(3)	(4)	(5)	(6)
	Young	Young	Young	Young	Older	Same state
Same Czone	0.046**	0.044**	0.034*	0.038*	0.033*	
	(0.020)	(0.021)	(0.020)	(0.020)	(0.019)	
Same Tract		0.0045	0.001	0.002	-0.026	0.008
		(0.024)	(0.023)	(0.016)	(0.022)	(0.015)
Unemployment			0.010	0.003	-0.004	0.004
			(0.028)	(0.019)	(0.021)	(0.019)
Same State						0.032
						(0.022)
Observations	204,281	204,281	190,197	190,197	145,325	190,197
R-squared	0.003	0.003	0.084	0.037	0.0008	0.037
Demographic controls	NO	NO	YES	YES	YES	YES
Year FEs	NO	NO	YES	YES	YES	YES
Individual FEs	NO	NO	NO	YES	YES	YES
Number of individuals	3,239	3,239	3,188	3,188	2,133	3,188

Robust standard errors in parentheses

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

Source: Panel Study of Income Dynamics

Table 6: Same Industry as Parents for Young Workers

Source: Panel Study of Income Dynamics 1968-2013
Note: Young workers (25 to 35 year olds) living in the same commuting zone as their parents are more likely to be employed in their parents' industry than young workers who live farther away.

A Appendix: Placebo Tests (For Online Publication)

Some placebo tests using the control group also show how the reweighting allows us to find groups with similar earnings paths around displacements. Another way to examine the reweighting approach is to plot the earnings trajectories of each control group, suitably reweighted. We do this in Figure 8 by plotting average earnings before and after years where they were at risk of a displacement, according to our definition, but where they did not actually lose a job. Using standard longitudinal weights, there is a large difference in initial earnings, and people who live farther from their parents tend to have steeper earnings trajectories that level off later than those of people who live close to their parents. These differences swamp the size of displacement losses, even for people who lose their jobs.

When we apply the weights, however, the earning dynamics are similar, and statistically indistinguishable except at the very end. Figure 8 shows that the two trends are lined up before the displacement, as shown in the earlier table, which is not surprising. Even from period zero (the simulated displacement) to period eight, when no information appears in the weighting procedure, the earnings trends track each other quite well. This implies that matching on initial earnings, education, occupations, gender, and other factors is enough to find workers with similar employment prospects.

In periods nine and ten of Figure 8, there are differences between the two groups, however. We have no easy way to understand exactly what is causing these differences. However, one intuitive reason for the slowdown, could be a causal relationship between living close to one's parents and expectations of care giving as parents age. This would match fairly well the fact that our sample of workers would be at least 35 years old ten years after the first possible displacement they could experience.

Since the reweighting does not perfectly control for worker's expected earnings trajectories, we control for these differences in the regression specification as best we can. In the regression specifications, as before, we include a quartic in workers' ages, interacted with whether they are in the group living close to or far away from their parents. Figure 8 shows these averages after removing the age quartic. Not surprisingly, the differences that remain between the two groups are quite small.

B Appendix: Including additional interactions in the baseline regression (For Online Publication)

To complement our reweighting approach, we also examined the effects of including interactions with other baseline characteristics, in the same way we separate out the effect of being closer to one's parents. We take another characteristic X_{ia}^C, like the person's earnings before displacement, and interact it with both the age quartic and the displacement dummies.

$$y_{iat} = \alpha_{ia} + \gamma_t + X_{iat}(\beta^A + \beta^H H_{ia}) + \beta^C X_{ia}^C) + \sum_{k=-4}^{10+} (D_{it}^k \delta^k + D_{it}^k H_{ia} \zeta^k + D_{it}^k X_{ia}^C \xi^k) + \epsilon_{iat} \quad (3)$$

The fixed effect, α_{ia} already controls for an effect of X_{ia}^C that is constant across time, but the additional interactions also control for time varying effects around the displacement. For example, if earnings losses are bigger after layoffs from jobs that pay more, then this would be reflected in negative values of ξ^k for $k > 0$. If this were driving our result that workers who live closer to their parents suffer smaller earnings losses, then including this term would also move the value of ζ^k closer to zero.

As before, the effects of a displacement for different groups are different linear combinations of δ^k and ζ^k terms, and we plot these as a simple way of understanding the impact of these policies. We plot $\delta^k + \zeta^k$ as the effect for people living near their parents and δ^k for people living farther from their parents. Since we are not including the ξ^k terms, the effect is for the omitted group where X_{ia}^C is a dummy variable and the value at the mean of X_{ia}^C, since we de-mean X_{ia}^C when it is a continuous variable. Note that the difference between the two lines is, due to functional form, unchanged regardless of the value of X_{ia}^C.

Figure 15 shows the coefficient estimates with several different interactions. The solid lines, reproduced from Figure 2, show the baseline for people living in the same tract as parents (darker line) and people living away from parents (lighter line). The 95th percentile of the distribution of the baseline is shown by the very slightly shaded portion surrounding each solid line.

The dashed, dotted, and dash-dotted lines in b and a of Figure 15, show the same coefficient plot if once also allows effects to vary by how remunerative the person's jobs was before displacement.[26] Controlling for initial incomes generally makes the initial earnings losses much more similar between people at different distanced from their parents. Controlling for income, however, does little to the finding that the two paths diverge later on.

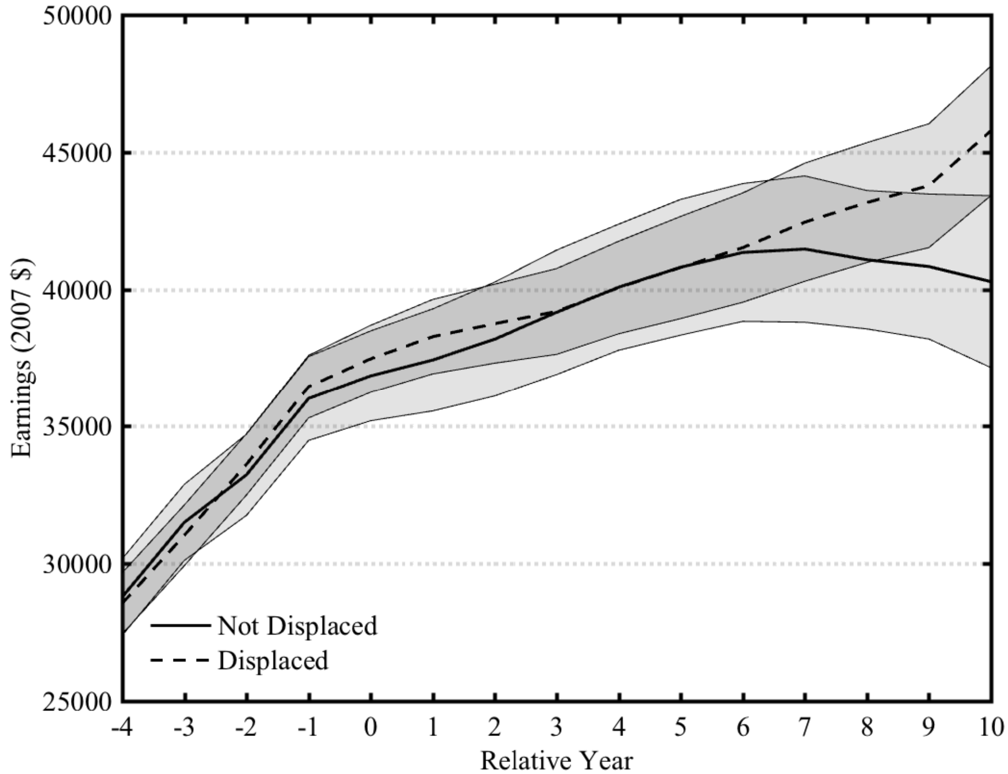
A possible interpretation is that initial losses seem mostly related to the job that was lost. Longer term effects, however, do appear to be affected by someone's proximity to their parents. this would be the case if the effect of local resources cumulated over time.

C Appendix: Reweighting and Restricting to Observations with Common Support (For Online Publication)

To ensure that we are working with a group of people, living near their parents, where we can find similar enough people living farther away, we use the procedure suggested by Crump et al. (2009) to restrict the sample and perform our reweighted analysis on this group.

[26] Each variable that we interact with is measured in the year before displacement, so earnings are for two calendar years before the current interview. The timing of these earnings vs the layoff will vary, and they may be over a year before the person was laid off.

(a) Unadjusted means



(b) Means after removing a separate age quartic for each group

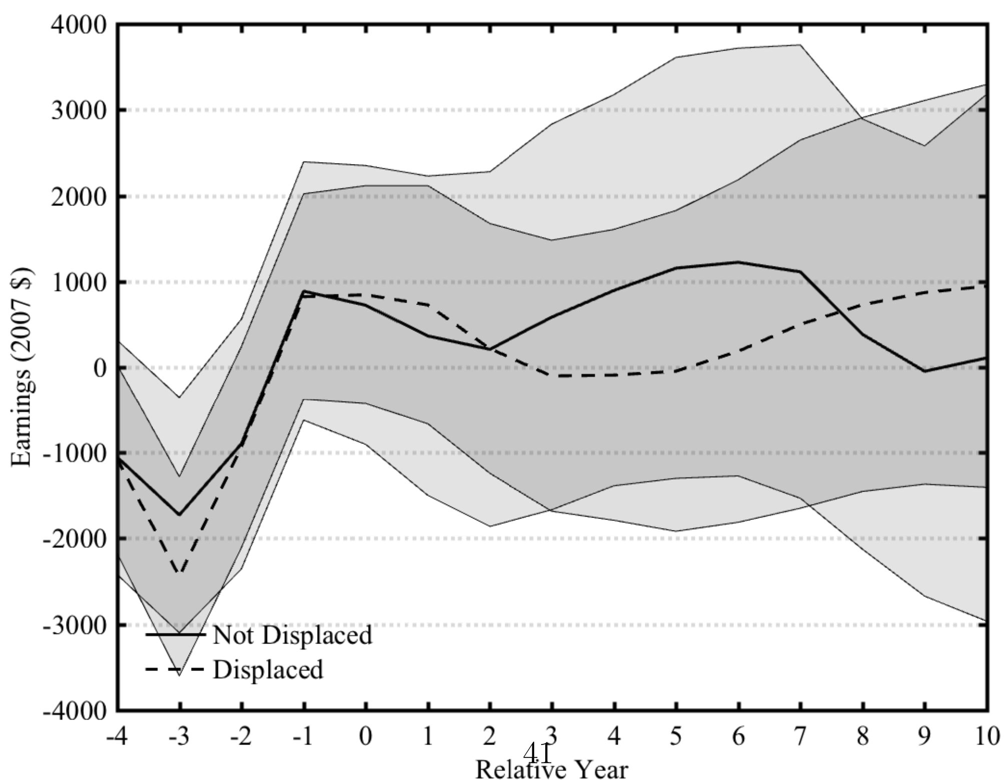


Figure 8: Means around "displacements" for the reweighted control samples

NOTES:

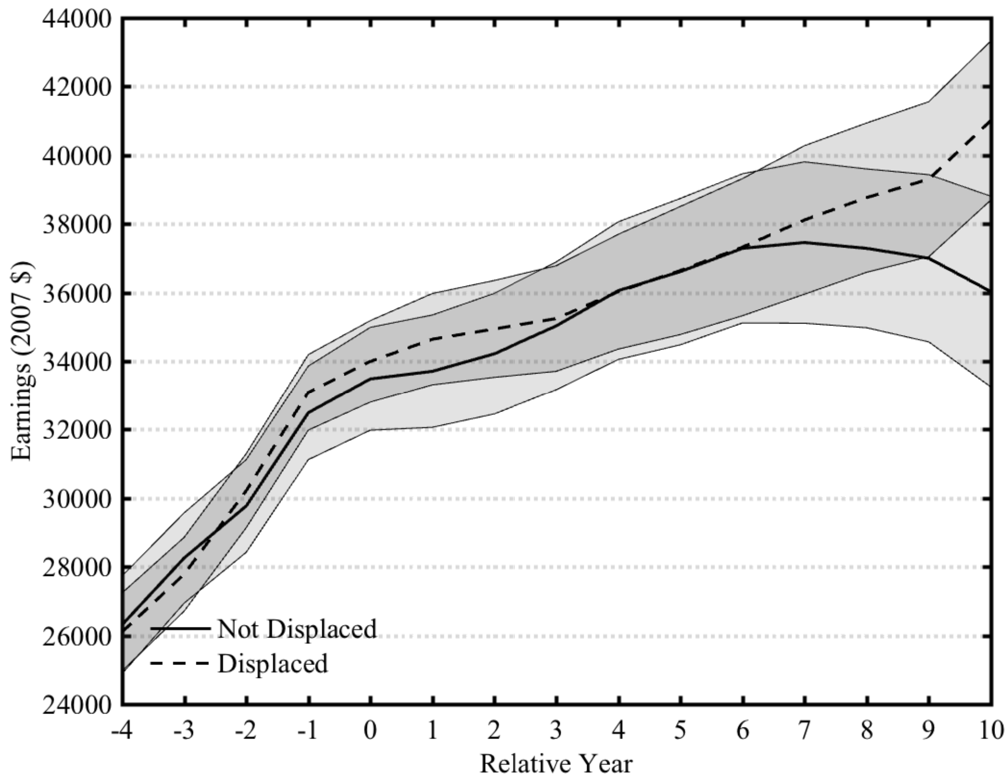


Figure 10: Means at baseline for the reweighting on observations with common support

NOTES:

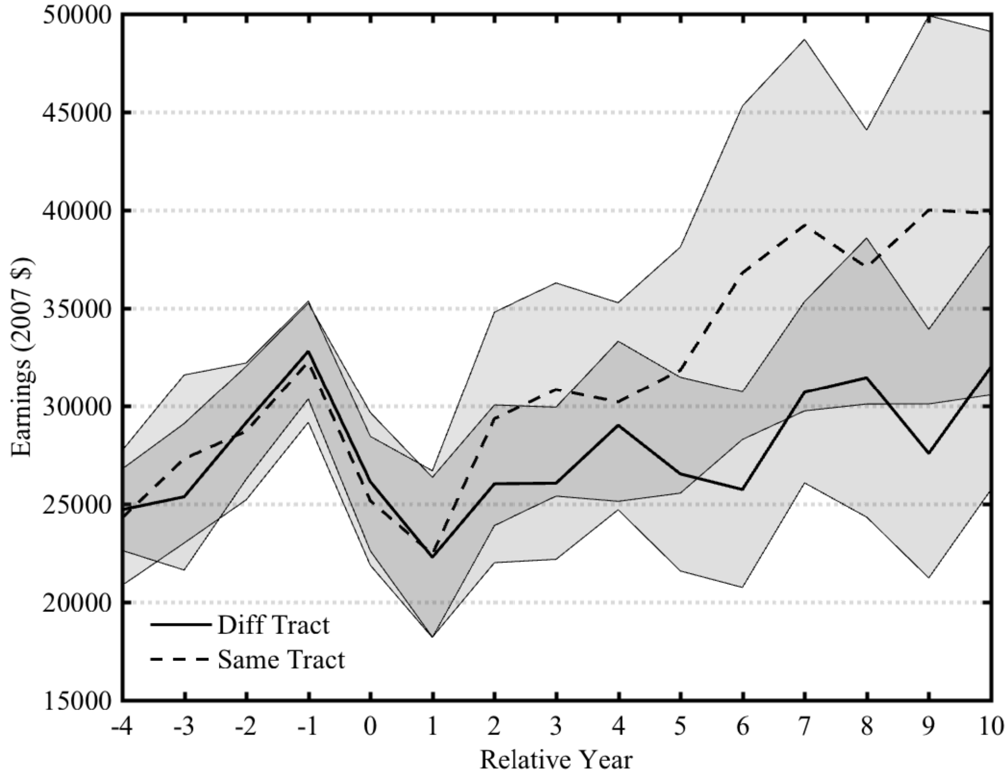


Figure 11: Means at baseline for the reweighting on observations with common support

NOTES:

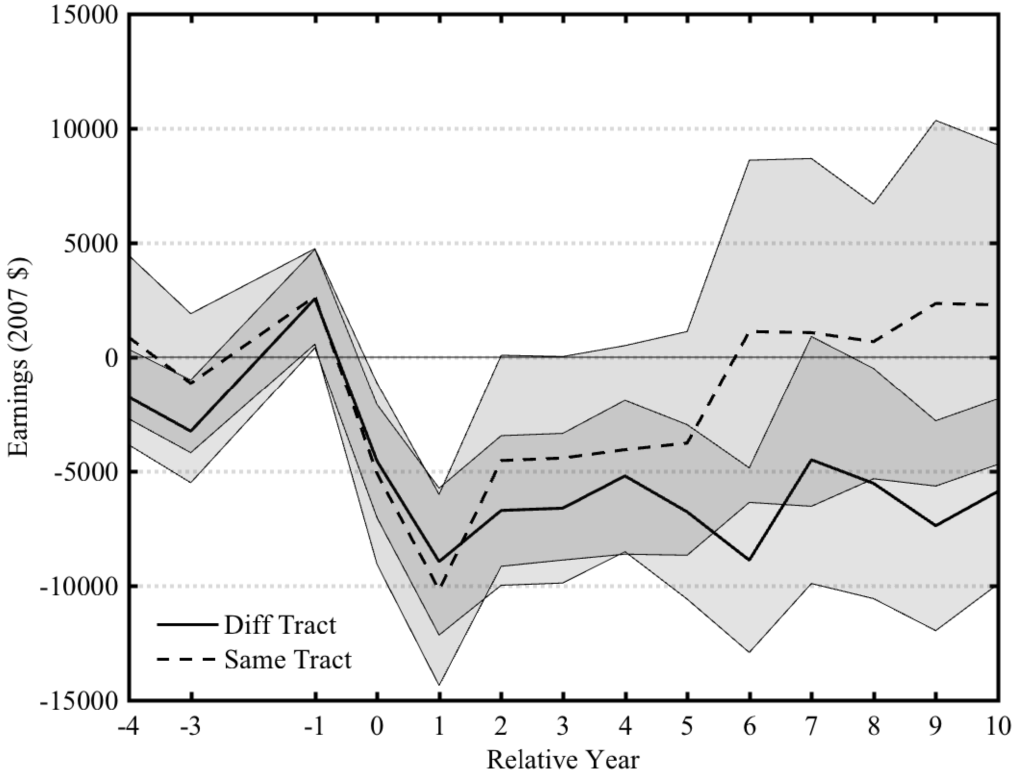
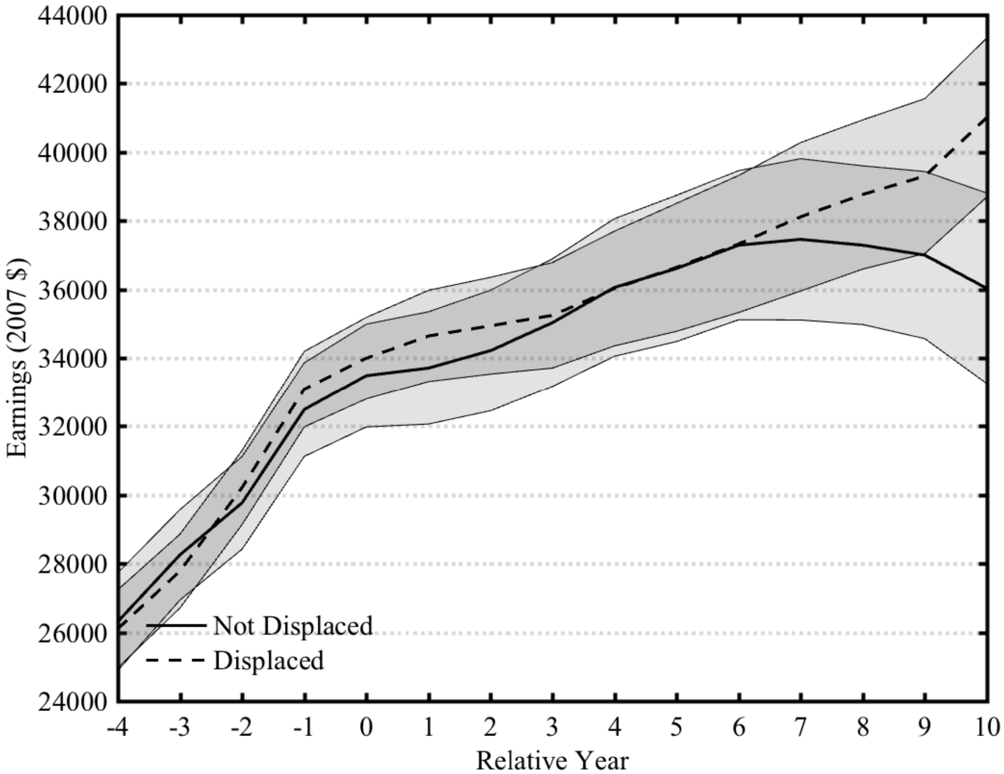


Figure 12: Regression results after reweighting only observations with common support

NOTES:

(a) Unadjusted means



(b) Means after removing a separate age quartic for each group

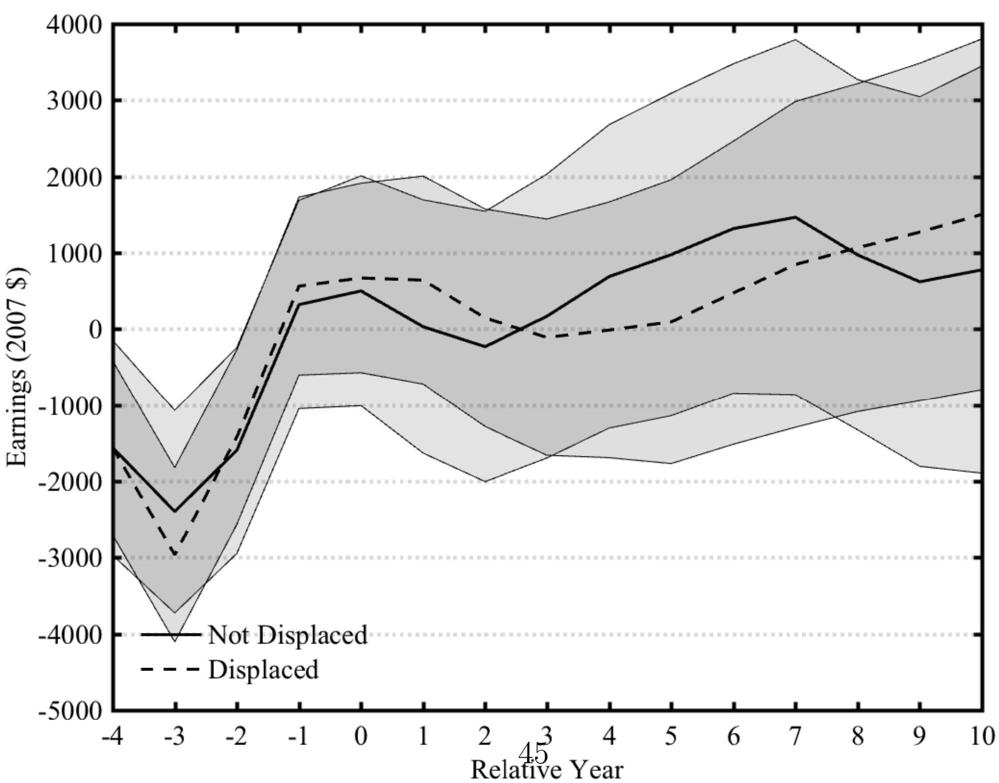


Figure 13: Means around “displacements” for the reweighted control sample fulfilling the common support condition

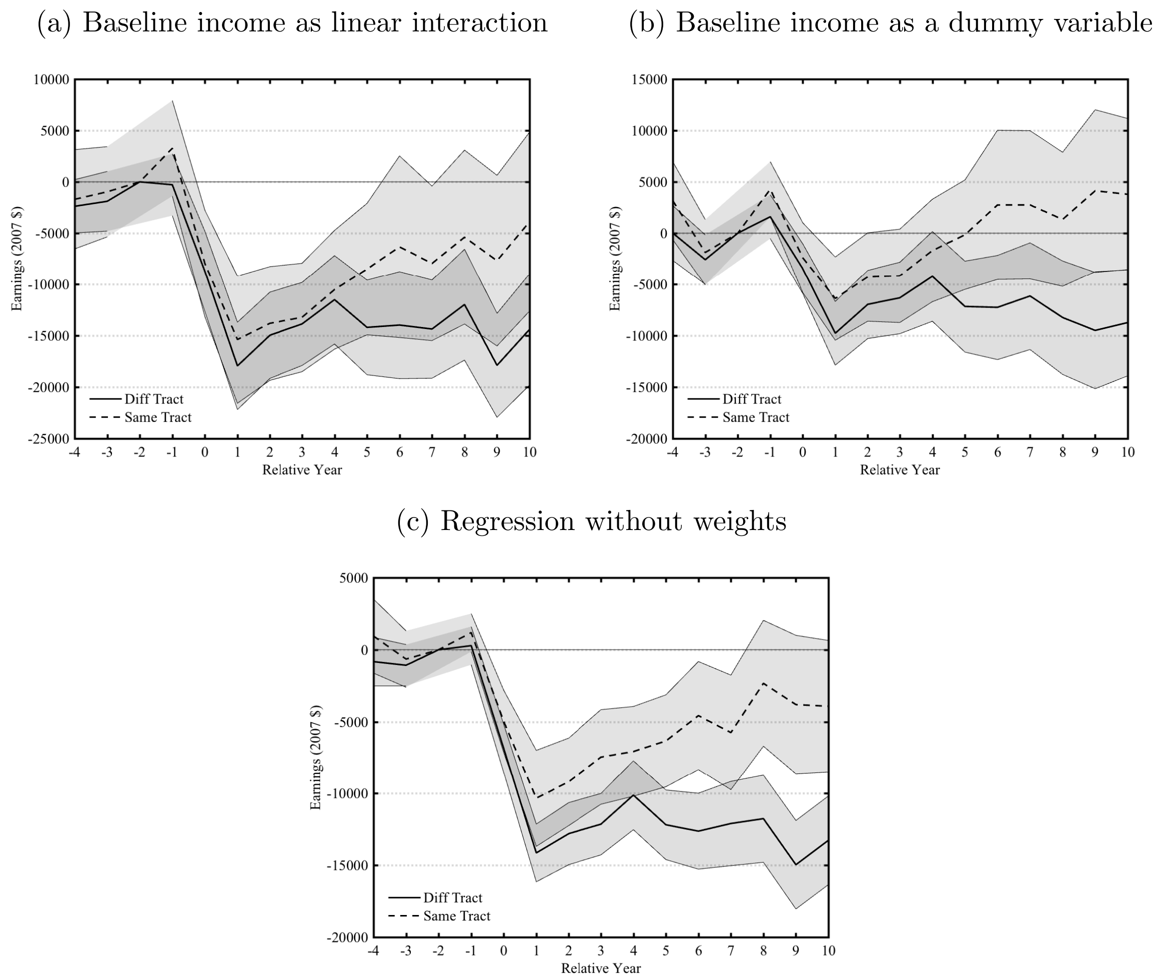


Figure 15: Including interactions in the baseline specification

NOTES: Each plot is a (combination of) regression coefficient[s] from a pooled panel regression of income on real earnings (in 2007 dollars). The dashed lines are the effect for people who lose their jobs while they live in the same census tract as a parent (in the PSID sample). Solid lines are for people who live in different tracts. The light grey liners represent 95 percent confidence intervals around the lines, computed using standard errors that are clustered by person.

	PSID weights				Re-weighted			
	Same tract		Diff tract		Same tract		Diff tract	
Variable	Displaced	Control	Displaced	Control	Displaced	Control	Displaced	Control
Income	29,414	32,791	32,692	35,695	29,414	30,116	29,068	30,334
	(1626)	(684)	(1072)	(468)	(1626)	(645)	(1306)	(519)
	1.00	0.00	0.00	0.00	1.00	0.79	0.80	0.86
Avg chg in income	2,461	1,684	3,494	2,385	2,461	2,025	3,816	2,342
	(629)	(174)	(458)	(120)	(629)	(189)	(570)	(159)
	1.00	0.50	0.83	0.27	1.00	0.61	0.32	0.87
Yrs of education	11.63	12.10	12.39	12.48	11.63	11.87	12.10	11.84
	(0.22)	(0.09)	(0.16)	(0.07)	(0.22)	(0.09)	(0.17)	(0.11)
	1.00	0.00	0.00	0.00	1.00	0.68	0.36	0.75
Avg. tenure	5.16	6.45	4.66	5.76	5.16	5.42	4.94	5.26
	(0.30)	(0.17)	(0.23)	(0.11)	(0.30)	(0.13)	(0.27)	(0.11)
	1.00	0.00	0.83	0.02	1.00	0.56	0.66	0.99
Share manager/professional	0.13	0.15	0.19	0.16	0.13	0.14	0.13	0.11
	(0.04)	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.03)	(0.01)
	1.00	0.03	0.00	0.00	1.00	0.75	0.88	0.96
Share in goods industries	0.54	0.48	0.49	0.41	0.54	0.50	0.50	0.44
	(0.06)	(0.03)	(0.04)	(0.02)	(0.06)	(0.03)	(0.05)	(0.02)
	1.00	0.04	0.51	0.00	1.00	0.26	0.56	0.03
Age	28.67	29.29	28.88	28.95	28.67	28.60	28.49	28.67
	(0.30)	(0.11)	(0.24)	(0.08)	(0.30)	(0.10)	(0.23)	(0.10)
	1.00	0.00	0.02	0.00	1.00	0.68	0.70	0.76
Share male	0.82	0.78	0.83	0.85	0.82	0.81	0.75	0.82
	(0.05)	(0.02)	(0.04)	(0.01)	(0.05)	(0.02)	(0.06)	(0.02)
	1.00	0.52	0.41	0.32	1.00	0.82	0.36	0.93
Avg num children	1.11	1.26	1.16	1.13	1.11	1.21	1.25	1.24
	(0.14)	(0.06)	(0.12)	(0.04)	(0.14)	(0.06)	(0.12)	(0.05)
	1.00	0.41	0.70	0.33	1.00	0.74	0.80	0.81
N	145	2574	235	4682	145	2574	235	4682

Table 7: Means of reweighted common support sample

NOTES: This reports means for each group in the sample with common support using PSID weights in the first four columns and the propensity score reweights in the last four columns. For each variable, we report the mean, the standard error f that mean, and a p-value of a Wald test that this mean is the same as the value in the first column. Standard errors and p-values adjust for clustering at the individual level.