
LONGITUDINAL EMPLOYER - HOUSEHOLD DYNAMICS

TECHNICAL PAPER NO. TP-2002-11

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Date : August 2002
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Abandoning the Sinking Ship: The Composition of Worker Flows Prior to Displacement¹

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August 2002

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Abstract

One of the most striking facts to emerge from the literature on displaced workers is the earnings declines experienced by workers several years before displacement occurs. Little attention, however, has been paid to other changes in compensation and employment in firms prior to the actual displacement event. This paper examines changes in the composition of job and worker flows before displacement, and compares the “quality” distribution of workers leaving distressed firms to that of all movers in general.

More specifically, we exploit a unique dataset that contains observations on all workers over an extended period of time in a number of US states, combined with survey data, to decompose different jobflow statistics according to skill group and number of periods before displacement. Furthermore, we use quantile regression techniques to analyze changes in the skill profile of workers leaving distressed firms. Throughout the paper, our measure for worker skill is derived from person fixed effects estimated using the wage regression techniques pioneered by Abowd, Kramarz, and Margolis (1999) in conjunction with the standard specification for displaced worker studies (Jacobson, LaLonde, and Sullivan 1993).

We find that there are significant changes to all measures of job and worker flows prior to displacement. In particular, churning rates increase for all skill groups, but retention rates drop for high-skilled workers. The quantile regressions reveal a right-shift in the distribution of worker quality at the time of displacement as compared to average firm exit flows. In the periods prior to displacement, the patterns are consistent with both discouraged high-skilled workers leaving the firm, and management actions to layoff low-skilled workers.

JEL codes: J65 (plant closings) J31 (wage differentials) J63 (turnover, layoffs)

Keywords: displaced workers, worker flows, quantile regression, fixed effects, longitudinal matched data.

1 Background and Motivation

One of the most striking facts to emerge from the literature on displaced workers is that not only do high-tenure workers suffer persistent earnings losses *after* losing jobs due to mass layoffs or plant closure, but that earnings declines for such workers are typically manifest up to several years *before* displacement occurs.¹ Some of this decline has been attributed to differences in unobserved characteristics between the ultimately displaced workers and the comparison group, continually employed workers, or to differences in the productivity of the firms/establishments that ultimately shut down. Jacobson, LaLonde, and Sullivan (1993) find that displaced workers and non-displaced workers possess equivalent observable characteristics, and conclude that pre-displacement losses “should be interpreted as losses due to [...] the events that led to the workers’ displacement” (Jacobson, LaLonde, and Sullivan 1993, pg. 691), and not to worker characteristics.

Little attention, however, has been paid to other changes in compensation and employment in firms prior to the actual displacement event. It seems reasonable to assume that the displacement does not come as a complete surprise to either management or workers. Prior knowledge, however, implies the possibility of action by both parties before displacement occurs. Management can hire and fire, workers can quit. This paper examines changes in the composition of job and worker flows before displacement, and compares the “quality” distribution of workers leaving distressed firms to that of all movers in general.

More specifically, we use longitudinal employer-employee data based on state unemployment insurance wage records, and combined with survey data, to decompose firm-level

¹See Jacobson, LaLonde, and Sullivan (1993) for Pennsylvania, Margolis (1999) for France, Lane, Miranda, Spletzer, and Burgess (1999) for Maryland. Schoeni and Dardia (1996) do not find pronounced earnings declines for workers in some industries in California. Fallick (1996) and Farber (1999) provide overviews of the literature on displaced workers.

jobflow statistics according to skill group and number of periods before displacement. In addition, we use quantile regression techniques to analyze changes in the skill profile of workers leaving distressed firms. Throughout the paper, our measure for worker skill is derived from person fixed effects estimated using the wage regression techniques pioneered by Abowd and Kramarz (2000) combined with the standard specification for displaced worker studies (Jacobson, LaLonde, and Sullivan 1993). Because person effects measure the labor market valuation of all time invariant personal characteristics, and are computed in conjunction with firm specific compensation factors, they can be interpreted as a measure of general human capital.²

The literature on job creation and destruction (Davis, Haltiwanger, and Schuh 1996) has documented extensive job reallocation even in industries with declining employment. At the firm level, recent work by Lengermann (2000) has shown that substantial differences exist with respect to the quality of job and worker flows in declining firms as compared to expanding firms. Since displacement is the limit case of a decline in employment, these differences may be even more pronounced in the time before a large single-period displacement.

The decline in employment, possibly ending in displacement, is typically a symptom of some difficulties at the firm: management, production, or demand problems. Typically, management will try to react to these difficulties, and the displacement, if less than total, may be seen as a final desperate attempt to salvage some part of the firm. The closing of the firm is obviously a sign of failure. However, it is also likely that management will try to resolve the problems in a less drastic fashion before resorting to the ultimate tool of mass layoff, of which the negative impacts on work morale have been subject of extensive study in the HR literature³, by selectively laying off bad workers, specifically trying to hire good

²See Abowd, Lengermann, and McKinney (2002) for a more thorough discussion of this approach.

³See Armstrong-Stassen (1993), Brockner (1990), Brockner, Wisenfeld, and Martin (1995), Konovsky

workers, and generally improving the quality of the workforce.

However, workers may also behave strategically upon learning of ongoing or impending difficulties at the establishment. In particular, some workers may become discouraged, others may decide to pursue a more promising career elsewhere. The Worker Adjustment and Retraining Notification Act (WARN), implemented in 1988, specifies 60 days of advance notice of mass layoffs. However, a BLS survey (Brown 1987), done before the introduction of WARN, found that while about half of all workers received advance notice on average 18 days before the layoff, over a third of layoffs received warning on average 46 days in advance. The consensus in the HR literature, based on the concept of organizational justice (Brockner, Wisenfeld, and Martin (1995), Konovsky and Brockner (1993)) and thus procedures, is that communication prior to the mass layoff can diminish, if not avoid these negative effects (Tang and Fuller 1995), implying that workers learn about impending layoffs before they occur. Extrapolating from Brown (1987), it is likely that workers have between 60 and 150 days of advance knowledge of impending layoffs⁴.

Gibbons and Katz (1991) describe a model in which a worker's ability is inferred from his past job history. Laid-off workers are thus inferred to be of lesser quality, whereas displaced workers escape this inference. Here, we have in mind an extension of this model in which the incentives facing workers prior to a displacement differ according to their ability. Better workers may seek to avoid being viewed as being of average quality by leaving the firm prior to the displacement, while those of lesser quality have an incentive to wait until

and Brockner (1993), and Tang and Fuller (1995), *inter alia*. Most of these studies concentrate on the effects on survivors of downsizing, after the fact. They note f.i.that "surviving employees often experience significant changes in corporate loyalty, job satisfaction, and job performance" (Tang and Fuller 1995) leading to productivity losses and "increased turnover among a firm's most valuable employees" (Konovsky and Brockner 1993, pg. 137).

⁴The lower estimate is based on the legal requirement, though there are caveats to its application. The higher estimate is the pre-WARN ratio of advance knowledge to advance notice ($46/18 = 2.5$), times the legal requirement.

the displacement occurs. To the extent that such a phenomenon outweighs the efforts of distressed firms to retain good workers and shed bad workers, we may observe the quality distribution of workers leaving firms prior to displacement lies to the right of the distribution of workers leaving healthy firms. Regardless, the competing agenda of discouraged workers and striving management can both lead to changes in quality of the workforce. We analyze these hypothesized changes by characterizing the skill level of workers moving in and out of firms.

Our results indicate that there are significant changes to all measures of job and worker flows prior to displacement. In particular, churning rates increase for all skill groups, while retention rates fall for high-skilled workers. The quantile regressions confirm a right-shift in the distribution of worker quality at the time of displacement as compared to average firm exit flows. In the periods prior to displacement, the patterns are consistent with both discouraged high-skilled workers leaving the firm, and management actions to layoff low-skilled workers.

The paper proceeds as follows. In Section 2 we describe the data and show how it constrains our empirical specification, which is presented in Section 3. Finally, results using firm-level jobflow statistics are presented in aggregate in Section 4.1 and then further disaggregated in Section 4.2. Section 5 concludes.

2 Data

We use unemployment insurance (UI) records from the state of Maryland for the period 1985:2 - 1997:2.⁵ As such, we have quarterly earnings records for essentially the entire

⁵Maryland UI data has also been analyzed recently by Burgess, Lane, and Stevens (2000), (Haltiwanger, Lane, and Spletzer 1999), and Lane, Miranda, Spletzer, and Burgess (1999). The data have been constructed as part of the Longitudinal Employer-Households Dynamics Program at the U.S. Census Bureau. Data from

universe of workers in the state, all matched to their respective employers. Only a tiny fraction of workers in jobs not subject to state employment taxes are missed. This includes Federal employees, self-employed individuals, and employees of small agricultural enterprises, and philanthropic or religious organizations. Individuals who receive no salary, who are completely dependent on commissions, and who work with no fixed location or home base are also excluded. One can thus build a precise picture of the sequencing of employment in conjunction with earnings at each job. Worker flows can be distinguished from job flows, and firms will be more than sufficiently connected by mobile workers to permit the simultaneous estimation of person and firm fixed effects.

It is also possible to construct the complete distribution of earnings within each firm. While Maryland UI records are top-coded, the fact that this is done quarterly rather than annually suggests that this should rarely be a binding constraint. Total wages including tips, commissions, and bonuses are covered up to a quarterly maximum of \$100,000.⁶ The raw data contain 105,613,487 observations for 5,098,206 individuals working for 262,441 firms.

For all of our empirical work, and following JLS, “firm” refers to the UI reporting unit, namely the state Employer Identification Number (SEIN). Just as an employer may have multiple establishments, so too may it have multiple SEINs (tax considerations unknown to the researcher determine this). At the same time, SEINs and establishments are not equivalent entities. For instance, a supermarket chain may choose to associate a single SEIN with each store, while retail store might choose to lump several stores into a single SEIN⁷.

several other states are presently available but arrived too late for inclusion in this draft. See Abowd, Lane, and Prevost (2000) or Vilhuber (2002) for more detailed descriptions.

⁶According to the *BLS Handbook of Methods* (1997), UI wage records measure “gross wages and salaries, bonuses, stock options, tips, and other gratuities, and the value of meals and lodging, where supplied.” They do not include OASDI, health insurance, workers compensation, unemployment insurance, and private pension and welfare funds.

⁷As discussed later, our empirical specification of displacements tries to take this into account.

This example aside, more than 90% of EINs are single-establishment entities.

Basic demographic information (age, race, and sex), while not available on the UI records, was obtained from other Census administrative data. After eliminating all observations with missing earnings, age, and sex information, the analysis sample used in our estimation of person and firm effects contains 98,726,271 observations for 4,539,451 workers and 256,105 firms. By comparison, Schoeni and Dardia (1996), who study workers displaced from the aerospace and durable goods manufacturing sectors in California, focused on 833,000 workers over a six year period (1989-1994). JLS studied the earnings of approximately 23,000 high tenure Pennsylvania workers over a thirteen year period (1974-1986). Additional sample restrictions on firm size and worker tenure are imposed in subsequent analyses of job and worker flows and displacement episodes, and are described in greater detail in Sections 3 and 4.

Because UI records do not distinguish full-time work from part-time work, both Anderson and Meyer (1994) and Burgess, Lane, and Stevens (2000) chose to restrict their analysis to full quarter employment. Under the full quarter assumption, a worker is counted as working for a firm in period t if and only if she appears at the same firm in periods $t-1$ and $t+1$. We chose *not* to adopt the full quarter assumption. The procedure drops a large number of low skilled workers who are consistently attached to the labor force but change jobs frequently. In future work, it should be possible to use a secondary dataset like the CPS to predict an individual's labor force attachment based upon variables common in both datasets. This could then be use to weight the observations in our earnings regressions.⁸

Our dataset shares a number of advantages as well as a few disadvantages of previous

⁸Burgess, Lane, and Stevens (2000) and Lane, Miranda, Spletzer, and Burgess (1999) also require workers to earn at least of 70% of what could be earned working full time at the minimum wage. We do not impose a similar restriction.

work on displaced workers using unemployment insurance records. On the positive side, it provides an extremely large sample of displaced workers whose earnings can be tracked over relatively long periods of time both before and after displacement, at least with respect to more traditional micro datasets such as the Displaced Worker Survey, PSID, and NLS. Furthermore, information on firm employment changes as well as individual earnings should be relatively free of measurement error. On the minus side, our analysis is limited to a single state, demographic information is limited, and layoffs cannot be distinguished from quits. A particularly prominent non-reported item is hours worked. As such, earnings changes resulting from a wage increase cannot be distinguished from changes stemming from increased labor force attachment. We also cannot determine why individuals transition from employment to measured non-employment. Such transitions could occur for a wide number of reasons—childbirth, retirement, layoff, injury, illness, death, or simply moving out of state—but is impossible to distinguish between them here.

Table 1 presents basic summary statistics for our sample of workers, while Table 2 describes the entire sample of 98.7 million person-firm-year-quarter observations. The statistics are calculated for all workers, workers displaced at least once, and workers who were never displaced. Since JLS studied workers with at least 6 years of tenure at the time of displacement from firms in Pennsylvania, we also present summary statistics for a similar group in our data. Because we do not observe a worker’s initial experience and do not currently have education data to calculate potential experience as a proxy, Table 2 reports “incremental experience,” which is an updated count of quarters observed in the data for each individual since their first appearance. In our earnings regressions, initial experience will therefore be absorbed into the person fixed effect in our earnings.⁹

⁹A related problem is that tenure is left-censored. In future work, we will assign education through statistical match for the majority of workers who cannot be linked directly to the Current Population Survey

3 Methodology

In this paper, we define a “displacement” as a substantial ($> 30\%$) reduction in a firm’s workforce from one (calendar year) quarter to the next. This differs from other definitions used in the literature. In particular, JLS, using similar data, defined as part of a “mass layoff” all workers who lost their job prior to a substantial drop in employment at their firm,” where the “substantial drop” is defined as “30-percent of more below [the firm’s] maximum employment in the late 1970’s.” (Jacobson, LaLonde, and Sullivan 1993, pg. 688) Our definition is more precise in that we associate employment reductions with current employment. Furthermore, since our data does not permit us to identify single establishments within the larger aggregate of the firm, our definition is designed to capture the closure of an establishment with high likelihood¹⁰. The disadvantage is that we may be capturing some seasonal fluctuations, since repeated “displacements” are more frequent. We will also at times refer to “distressed” firms. This will be understood to refer to firms that will generate displacement in the near future.

We label a worker as “displaced” if he left the firm in the quarter in which the substantial reduction occurred. Dummy variables for up to 2.5 years (10 quarters) prior to displacement are then constructed. Going beyond the existing literature, we also flag workers that worked for distressed firms, but who left *prior* to the displacement quarter. We identify such workers up to 10 quarters before the actual displacement, and construct the same dummy variables as above, up to the point in time where they leave the firm¹¹.

More formally, denote the set of dummy variables capturing the effect of (future/past)

(CPS) or the Survey of Income and Program Participation (SIPP).

¹⁰Alternately, the term “displacement” could be replaced by “downsizing.”

¹¹This is not yet implemented for the wage regressions.

displacement by DI_{it} . In the notation of JLS,

$$DI_i' \delta = \sum_{\tau \geq -m} DI_i^\tau \delta_\tau, \quad (1)$$

where DI_i^τ is unity if displacement occurred in τ periods (if $\tau \leq 0$, then displacement occurs in the future), m denotes how many periods in advance this vector of dummies is started, and time subscripts t have been suppressed for convenience. For instance, δ_{-1} measures the effect of displacement that will occur in the next period on the present period's earnings.

Similar to the definition of DI , above, we also use an indicator vector $DJ = (DJ^\tau, -m \leq \tau \leq 0)$ to identify firms that will generate displacement in the future:

$$\begin{aligned} DJ_{it}^\tau &= I(\exists h \neq i : J(h, t) = J(i, t), \\ &DI_h^\tau = 1, \\ &J(h, t - \tau) = J(h, t)) \end{aligned} \quad (2)$$

where I is the usual indicator function. The function $J(k, t)$ is used to identify the firm for which worker k works in period t . DJ_i^τ captures the fact that worker i works in a firm in t that displaced at least one worker h in period $t - \tau$. In the present paper, τ is negative, denoting a displacement occurring in the future. Alternately, DJ_j^τ flags firms in which displacement will occur in τ periods. We will use one or the other notation interchangeably, depending on whether the analysis occurs at the level of the firm or the worker.

Using the dataset described in Section 2, we estimate an OLS regression controlling for both worker and firm unobserved heterogeneity (Abowd, Kramarz, and Margolis 1999), and

incorporating the displacement dummies DI :

$$w_{it} = X_{it}\beta + DI_i'\delta + \theta_i + \Psi_{j(i,t)} + \varepsilon_{it} \quad (3)$$

where w_{it} measures log earnings for individual i at time t , X_{it} are time-varying individual characteristics, θ_i measures the effect of time-invariant individual characteristics (“worker quality”), $\psi_{J(i,t)}$ is a firm-specific (productivity) effect on wages. $J(i,t)$ is defined as before, and ε_{it} is the statistical residual, uncorrelated with all the right hand side variables¹². In our data, X_{it} includes a quartic in incremental experience, year and quarter dummies (all of which are allowed to vary by gender)¹³.

From these regressions, we obtain firm fixed effects ψ and person fixed effects θ . Hence, viewed in this light, a worker’s wage is the sum of the market valuation of both her observable and unobservable personal characteristics (the external wage) and the specific compensation policies chosen by her employer (the internal wage). While Abowd, Lengermann, and McKinney (2002) discuss the merits of using person effects to measure skill relative to more traditional measures, it suffices to claim here that they proxy for general human capital, i.e. the portable component of an individual’s earnings. In subsequent analysis, we describe the distribution of person fixed effects in flows out of firms, controlling for possible displacement occurring at the employing firm up to 10 quarters in the future. We also disaggregate

¹²See Abowd, Kramarz, and Margolis (1999) for a more detailed description of this model. The computational algorithm used here (Conjugate Gradient) to obtain the person and firm fixed effects differs from the conditional methods described in that article. See Abowd, Creedy, and Kramarz (2002).

¹³The person and firm fixed effects can be each be further decomposed into a part related to time-invariant characteristics (education, race, sex, and initial labor market experience for individuals, tenure for firms) and a residual:

$$\begin{aligned} \theta_i &= \alpha_i + u_i\eta \\ \Psi_j &= \phi_j + \gamma_j s_{it} \end{aligned}$$

Note that by construction, $cov(\alpha_i, u_i\eta) = cov(\phi_j, \gamma_j s_{it}) = 0$ for all i and j .

jobflow statistics based on workers' positions in the overall distribution of person effects.

3.1 Specification 1: Job and worker flow statistics

Two issues surround job displacement and worker movements before the actual displacement. First, how do job and workers flows differ from the usual flows before displacement occurs? If our hypothesis on advance notice is correct, not only could there be net job destruction prior to the displacement event, but the workers generating those net outflows may be of higher quality, with higher outside opportunities, than the average quality of workers in normal turnover. This section analyzes changes in several job and worker flow statistics, while Section 3.2 considers the quality of worker outflows.

The primary specification in this section is

$$XFR_{jt} = \tilde{\psi}_j + \tilde{X}_{jt}'\tilde{\kappa} + DJ_j'\gamma^{XFR} \quad (4)$$

where XFR_{jt} is one of several job and worker flow statistics for firm j at time t , and $\tilde{\psi}_j$ captures firm-specific average levels in those statistics. γ^{XFR} maps out the changes in these statistics prior to the displacement event. X_{jt} is a set of year and quarter dummies to control for business cycle and seasonal effects in these rates.

Several statistics are standard in the literature (Davis and Haltiwanger 1999). *Job flows* for firm j are defined as the change in employment between two adjacent periods: $JF_{jt} = E_{jt} - E_{jt-1}$, where E_{jt} is employment at firm j at time t . *Accessions*, A_{jt} , are all workers employed in firm j in t , but not in $t - 1$, and *Separations*, S_{jt} , are all workers employed in firm j in $t - 1$, but not in t . Finally, *churning flows* (excess worker flows) CF_{jt} for firm j at time t are defined as $A_{jt} + S_{jt} - |JF_{jt}|$.

The following identity thus holds:

$$E_{jt} = E_{j,t-1} + A_{jt} - S_{jt} \quad (5)$$

Rates associated with such flows can be computed in two ways. The usual one would be with respect to current period employment, E_{jt} . This is used in the computation of displacement, which is always well-defined. However, for a number of reasons, we follow Davis, Haltiwanger, and Schuh (1996) and define a *symmetric rate* as

$$XFR_{jt} = \frac{XF_{jt}}{(E_{jt} + E_{j,t-1})/2} \quad (6)$$

where XF is one of JF, A, S, CF , as defined above. This yields a rate ranging between -2 and +2. These rates are then used in Equation (4).

3.2 Specification 2: Worker outflows

In order to properly describe the conditional distributions of worker quality in gross outflows, we employ quantile regression techniques. The general model is formulated as (Buchinsky 1998):

$$y_i = \tilde{z}_i' \tilde{\beta}_\omega + u_\omega, \quad Quant_\omega(y_i | \tilde{z}_i) = \tilde{z}_i' \tilde{\beta}_\omega, i = 1, \dots, n \quad (7)$$

where \tilde{z}_i is a K -vector of regressors, and $Quant_\omega(y_i | \tilde{z}_i)$ is the conditional quantile of y_i , conditional on the regressors \tilde{z}_i . In particular, for notational convenience, we partition \tilde{z}_i so that

$$y_i = z_i' \beta_\omega + DJ_i' \gamma_\omega + u_\omega. \quad (8)$$

The above regression can be repeated across quantiles (f.i., $\omega \in \{0.05, \dots, 0.95\}$), generating a set of coefficients that map out the effect of future displacement on the distribution of y_i , relative to the outflow at non-distressed firms¹⁴

In every time period t , define the set of workers OF_{jt} who at the end of the period (start of next period) no longer work for the same employer j as at the start of the period:

$$OF_{jt} = \{i | J(i, t) \neq J(i, t + 1)\} \quad (9)$$

The dependent variable at every cross-section is thus $y_{ijt} = \theta_i, i \in OF_{jt}$, the general human capital of a worker i leaving firm j in period t .

We then estimate the quantile regression

$$y_{ijt} = z_i' \beta_\omega + DJ_i' \gamma_\omega + u_\omega \quad (10)$$

Here, γ_ω is the vector of coefficients mapping out the change in the flow prior to the displacement event. A positive (negative) γ_ω^τ describes how much higher (lower) the appropriate quantile ω lies in the range of possible worker productivity values. z_i includes controls for gender, race, tenure, seasonal and year dummies.

Our motivation for using quantile regression analysis can perhaps be best explained by referring to Figures 1, 2, and 3. Figure 1 shows the case where the distribution of worker productivities in outflows from distressed firms is shifted upwards and has a higher variance. The mean (and median) effect is represented by the upper arrow, and would be captured by the usual OLS regression. However, the effect on the 90th percentile by far exceeds the effect at the mean. The lower mean effect hides the strong upward shift in the distribution.

¹⁴An alternative comparison group would be the group of never-distressed firms.

Figure 2 illustrates a more extreme example. Plotted are the differences at the 10th and the 90th percentile. Whereas the mean change in worker productivity is small and positive, the change at the 90th percentile is again much larger and positive, and the change at the 10th percentile is actually negative. Thus, the increase in the mean worker quality would mask a substantial increase in the variance of worker quality in outflows.

Rather than keeping the percentile constant, one can also interpret the results from a quantile regression at a constant level of human capital. In Figure 3, the outflow of workers from distressed firms again has a higher percentage of low quality workers as those in non-distressed firms, but also has a higher percentage of high quality workers, a fact that is hidden behind the small increase in mean human capital. In particular, if one expects advance notice and the discouragement effect to increase voluntary departures of high-quality individuals, and employment policy to increase the fraction of low-quality individuals laid off, then this is precisely the change in the distribution one would expect. By plotting the coefficients on the dummies denoting the distressed group as well as the effect of future displacement we can describe graphically (and analytically) the change in flows of workers of different quality.

4 Results

Since the focus of this paper is on the period prior to displacement, we only include dummies for the pre-displacement periods in Equation (3). Since all regressions include a full set of person fixed effects, the dummies show the change in quarterly earnings relative to time spent in non-distressed firms, which includes the post-displacement period. We implement the regression on two samples. The first includes all workers. The second, which we label “high tenure workers,” includes workers who were either never displaced but accumulated at least 6 years of tenure at one of their employers, or who were displaced but accumulated at

least 6 years of within-sample tenure by the time of the displacement¹⁵.

Figure 4 plots the coefficients from these regressions. Contrary to findings reported both by JLS and Margolis (1999), but consistent with the results in Schoeni and Dardia (1996), there is no evidence of a strong decline in earnings in prior to displacement. Although the point estimates indicate a small decline in the three quarters prior to displacement (6 for high tenure workers), JLS found substantial declines up to twelve quarters prior to displacement. Lane, Miranda, Spletzer, and Burgess (1999) find similar pre-separation earnings declines in earnings for all movers up to four quarters prior to separation, using the same data as this paper.¹⁶ In both samples, earnings fall by approximately 20 to 25 percent relative to their long-run values.¹⁷ However, this is approximately 35 to 40 percent below their earnings six quarters prior to displacement. Thus, as in previous research, we find that there are substantial earnings losses associated with displacement.

4.1 Job Flows and Displacement

Figure 5 plots the coefficients on the dummy variables (γ^{XFR}) produced by estimating Equation (4). The equation was estimated four times (one line per regression), so as to measure the effect of future displacement on the overall job flow, accession, separation, and churning rates of firms. Since the regressions control for both firm fixed effects as well as year and quarter effects, each coefficient can be interpreted as the deviation from the long run or

¹⁵JLS also use this restriction. Margolis (1999) imposes a 4-year tenure restriction for France, Schoeni and Dardia (1996) seem to impose a 2-year tenure restriction in practice.

¹⁶Their definition of a job relies on the full-quarter definition of jobs. While they do not simultaneously control for both worker and firm heterogeneity, they do include firm level variables.

¹⁷The baseline, however, includes post-displacement earnings. Due to our focus on the period prior to displacement, a worker's long-run earnings (her "productivity" or "ability", and the baseline here) is likely to be lower than in a less parsimonious specification. This is due to the fact that a workers estimated long-run earnings are computed based both on her earnings in the distressed firm more than 10 periods before displacement, and all her post-displacement earnings. Insofar as post-displacement earnings are typically below long-run earnings, our estimate would be downward biased.

average flow rate (normalized to zero) that would have occurred in the absence of future displacement. For example, when the job flow rate is the dependent variable, the dummy variable measuring whether displacement occurs in two quarters is approximately .1. This means that the average firm's job flow rate increases 10 percentage points above its long run, non-displacement rate.¹⁸ As expected, at the time of displacement, separation rates rise dramatically above average, and accession rates fall. Hence, overall job flow rates fall by an even larger amount.

Curiously, while job flow rates dip a year before displacement, they subsequently recover and actually rise steadily for several periods. This increase is the result of an even sharper increase in the accession rate and a roughly stable separation rate. One possible explanation for this phenomena is a serially correlated increase in single-period worker matches to distressed firms. Consider a distressed retail store with a fixed amount of job slots. If worker quits rise continually during the year leading up to displacement, the store will be forced to cycle more and more new workers through the same positions just to stabilize employment at a given point in time. Thus, the rising job flow rate could simply be an artifact of our current flow definition of employment. Recall E_{jt} counts all workers that appear in firm j during the *entire* period t .¹⁹ The fact that the churning flow rate also rises gradually in the periods leading up to displacement at least partially corroborates this hypothesis. Nevertheless, if increased single-period matches were the sole explanation why job flow rates rise prior to displacement, one would also expect above average, or at least rising, separation rates. If anything, the reverse is true.

¹⁸These coefficients were almost always statistically significant. This remains the case for Figures 6-9 where we decompose job and worker flows according to their skill composition.

¹⁹In the near future, we intend to replicate our results using alternate definitions of employment such as end of quarter (E_{jt} equals all workers employed in firm j at time t and $t + 1$) and full quarter employment (defined earlier in sec: data).

All of this aside, what we are really interested in addressing is not how overall job flows change in advance of displacement, but rather how the *composition* of these flows might vary along worker quality lines. Recall our conjecture that, in anticipation of possible future displacement, firms may attempt to dismiss their least productive workers and (possibly) recruit high skill workers. At the same time, if potential employers cannot perfectly observe worker quality, high skill workers at distressed firms may quit in advance of displacement in order to avoid being viewed as “average” in the post-displacement labor market. By the same logic, low skill workers may be less willing to quit, as being viewed as “average” may actually be advantageous. One way to examine this is to first decompose job and worker flows into skill categories based on workers’ positions in the distribution of person effects, and then to re-estimate Equation (4) for each category. Define

$$XF_{jt} = \sum_{k=1}^4 XF_{jt}^k, \quad (11)$$

where k references flows of workers in quartile k of the distribution of 4.5 million person effects, and XF is one of JF , A , S , and CF as before. The dependent variable is now

$$XFR_{jt}^k = \frac{XF_{jt}^k}{(E_{jt}^k + E_{jt-1}^k)/2} \quad (12)$$

for $k = 1, \dots, 4$. A firm’s overall flow rate can be obtained by summing the component rates weighted by their share of total employment.

In Figures 6 to 9, we distinguish the effects of future displacement on job and worker flows categorized according to these four skill groups. Group 1 refers to workers in the lowest skill quartile, Group 4 the highest. While the long run flow rates that would have occurred in the absence of displacement are again normalized to zero, it should be noted that the

actual rates vary considerably by skill group. In Maryland, accession and separation rates typically decline monotonically with skill.²⁰ Just as with overall job and worker flows, in the year leading up to displacement, accession rates rise above average, and separation rates are either stable or declining. Hence, job flow rates rise for all four skill groups. Notice, however, that between four and two quarters before displacement, job flow rates increase much more rapidly for low skill workers. While one cannot conclude for sure that during this period distressed firms become less skilled, it is true that their rate of upskilling (deskilling) declines (rises). In firms with equal job flow rates for high and low skilled workers (i.e., firms that have attained their steady state skill mix), the overall composition of employment does indeed become less skilled. In the following section, we return to this issue from a somewhat different perspective by asking how the quality distribution of workers leaving distressed firms differs from the distribution of all movers.

Another interesting result is that the effect of displacement on job flows in the period immediately preceding its occurrence actually declines relative to the previous period for the two lower skill groups but continues to rise for the higher skill groups. This does *not* mean that overall job flow rates converge across skill levels, but rather the increase in job flows above their long term rates becomes somewhat more uniform. While accession rates are above average for all four groups, the effect of displacement on accessions falls for Groups 1 and 2 but continues to rise for Groups 3 and 4 between the second and first period before displacement. At the same time, while Figure 5 showed that the overall separation rate dipped only slightly before displacement, once we decompose separations into their component parts, we see that the aggregate numbers actually mask above average separations

²⁰The economy wide quarterly accession rates in Maryland between 1985:2 and 1997:2 were 39%, 21%, 12%, and 8% for skill groups 1-4 respectively. In the same order, separation rates were 38%, 20%, 12%, and 8%. See Lengermann (2000) or Burgess et al. (2000) for more details.

for high skill workers but below average separation rates for low skill workers. Indeed, the decline in separation rates for lower skilled workers is particularly striking when viewed in light of their sharp upward spike just three periods earlier.

In summary, accession rates rise for all groups prior to displacement but separation rates fall below average only for the lower skilled. One explanation for these divergent patterns is that high skilled workers do indeed “abandon the sinking ship,” while the low skill workers “remain on board,” although we cannot know for certain as we cannot distinguish quits from dismissals. The decision to leave could be the result of advance knowledge/notice and, in the terminology of Gibbons and Katz (1991), reflect a desire to avoid being viewed as average by subsequent employers. In contrast, the decision to stay could reflect lower outside options for the less skilled, a higher valuation of severance pay, or a desire to be viewed as average in the post-displacement labor market.

Alternatively, above average outflows of high skilled workers could be a cause rather than a consequence of displacement. Figure 9 shows that churning rates in pre-displacement firms are considerably above average for all skill groups. Burgess, Lane, and Stevens (2000) outline a scenario in which excessive worker flows interfere with a firm’s ability to function properly and hence facilitate its demise. Unfortunately, our current empirical framework cannot distinguish between these competing hypotheses.

4.2 Worker Quality, Mobility, and Displacement

We next consider changes in the distribution of human capital for workers leaving distressed firms, by estimating Equation (8) on a sample comprised exclusively of movers.²¹ Because of the inherent volatility in the creation and destruction of small firms, we restrict our sample

²¹As mentioned previously, this includes movers from distressed and non-distressed firms.

to separations from firms that averaged at least 25 employees over all periods they appear in the data. Workers can and do contribute multiple observations, but only one per period. The resulting file has 5,850,843 observations, 15,852 firms, and 2,586,701 individuals²².

Figure 10 summarizes the results from the quantile regressions. Only estimates up to five periods prior to displacement are included, as estimates for longer periods were generally small and inconsistent. Panel (1) describes the distribution of worker quality (θ) in separations from all firms, distressed and non-distressed, for 20 quantiles, starting at 5 percent. Each bar reflects the value of the worker fixed effect at that specific quantile.²³ Note in particular the left-skewness of the distribution of worker quality in flows. For reference purposes, the distribution of worker effects in the population as a whole (movers and non-movers) is mean zero by construction (employment-weighted and unconditional) and has a third quartile of 0.75, a median of 0.20, and a first quartile of -0.38.

Each subsequent panel in Figure 10 plots the displacement coefficients associated with the periods leading up to the displacement event, as described in Section 3.2. The bars are the direct correspondence to the arrows in the Figures 1 and 2, which depicted the change in worker skill for each quantile. The horizontal line shows the mean effect, estimated by OLS regression using the same specification. It is useful to remember that a simple right- or left-shift, without a change in the distribution (a variance-preserving change in the mean), would result in all coefficients being identical and equal to the mean effect. On the other hand, a mean-preserving spread would have positive values for upper quantiles, and negative ones for low quantiles, with a mean change of zero. We bootstrapped tests of simultaneous

²²Due to computational restrictions, we further subsampled one out of two firms due to computational restrictions. The actual analysis file described below contains 2,951,792 observations on 1,767,055 individuals leaving 7,926 firms.

²³A rotation of this graph, with worker fixed effect on the horizontal axis, would correspond to a conditional cumulative distribution function.

equality of quantiles 0.05, 0.10, 0.90, and 0.95, for all coefficients, and all null hypotheses of equality were rejected at conventional levels.²⁴

First, and most notably, Panel (2) refers to the period of displacement and shows a strong right-shift at all quantiles. This implies that the distribution has a higher overall mean, and fewer low skilled workers relative to high skilled workers. The pattern here is consistent with a signaling model à la Gibbons and Katz (1991) but where bad matches are dissolved more often than good matches, and normal separation flows are predominately comprised of layoffs rather than quits.

Second, all panels show an upward trend of the coefficients across quantiles, consistent with an increase of variance (a thickening of the tails) of the quality distribution, as was illustrated in Figures 2 and 3. In particular, both low and high quality workers comprise a larger portion of total separation flows relative to workers near the median.

Some large and significant changes also occur one period prior to displacement. Contrary to the displacement period itself, the distribution of the worker outflows is left-shifted: Workers at every quantile are of lower quality. However, since the change in the upper quan-

²⁴The following test was repeated for every coefficient:

$$\begin{aligned} (q05 :)DJ_{it}^{\tau} - (q10 :)DJ_{it}^{\tau} &= 0.0 \\ (q05 :)DJ_{it}^{\tau} - (q90 :)DJ_{it}^{\tau} &= 0.0 \\ (q05 :)DJ_{it}^{\tau} - (q95 :)DJ_{it}^{\tau} &= 0.0 \end{aligned}$$

where (qxx:) denotes the coefficient from the quantile regression for quantile xx ($xx = 0.05, 0.10, 0.90, 0.95$). The results were as follows:

$$\begin{aligned} F^{\tau=0}(3, 2951767) &= 234.17 \\ F^{\tau=1}(3, 2951767) &= 4.80 \\ F^{\tau=2}(3, 2951767) &= 7.25 \\ F^{\tau=3}(3, 2951767) &= 118.71 \\ F^{\tau=4}(3, 2951767) &= 186.69 \\ F^{\tau=5}(3, 2951767) &= 571.33 \end{aligned}$$

tiles is smaller, the lower tails of the distribution have grown proportionately thicker. In other words, the ratio of low fixed effect workers to high fixed effect workers—for example, the ratio of the lowest quartile to the highest quartile—increases in distressed firms in the quarter before displacement.

Interestingly, in the 2 to 4 periods before displacement, while the change in the lower quantiles is negative, it is positive for some of the higher quantiles. Thus, not only are there more low and high skill workers relative to the median of that flow, but also relative to the separation flow of the typical firm depicted in the first panel. Hence, in comparison to Panel (1), panels Panels (4) to (6) suggest a mean-preserving spread in the distribution. Both low and high skilled workers leave distressed firms in higher proportions than medium skilled workers.

Panel (7) depicts coefficients for changes in job separation flows five periods before the displacement quarter. The most striking point here is the sharp expansion in the upper half of the distribution. The mean change in worker quality can almost entirely be accounted for by movements of high skill workers. Recall from the previous section (see Figure 8) that separation rates for higher skill groups exceeded those for the lower skill groups, at least in the three to five quarters before displacement. The finer disaggregation of those flows provided by Panels (5) and (7) suggests this phenomenon stretches out across the entire distribution of worker skill in separations. Since this pattern is observed five quarters before displacement, perhaps our story about prior knowledge is less relevant here. As noted in Section 1, an optimistic estimate on advance notice is 150 days, or approximately two quarters before layoff. Quite possibly, the strong changes observed more than a year in advance of layoffs may ultimately *cause* the firms' future distress. Clearly, further study is necessary to determine the extent to which large separations of high-skill workers predict

future firm distress.

Finally, it is important to keep in mind that the scale of the shifts depicted in Panels (2) to (7) is typically small relative to the overall level depicted in Panel (1). Figure 11 depicts the cumulation of effects in Figure 10, Panel (1) relative to the corresponding cumulations of effects in Panels (2) to (7). Apart from Panels (0) and (1) in Figure 11, the only noticeable differences of any magnitude occur in panels (3) and (5) in the upper quantiles.

5 Conclusion

The hypothesis entertained in this paper is that, given knowledge of future economic distress, both workers and firms may engage in strategic behavior to minimize the sizeable economic costs associated with displacement. However the competing agenda of managers and firms are actually resolved, it seems likely that not only may the flows of workers both into and out of firms change, but also the skill composition of these flows. We explored this prediction using a unique dataset that combines twelve years of quarterly unemployment insurance records with limited demographic information on individual workers. The large scale of our data allows us to paint a fairly precise picture of the sequencing of employment in conjunction with earnings at each job. As such, worker flows can be distinguished from job flows and person heterogeneity can be disentangled from firm heterogeneity. Furthermore, and most importantly, we can distinguish workers leaving firms *in advance* of mass layoffs.

Using two different approaches, we find consistent support for our hypothesis. By decomposing job and worker flow rates by skill group, we find that jobflow rates rise for all workers prior to displacement but that this increase is more pronounced for low skill workers, largely resulting from declining separation rates. On the other hand, separation rates for high skill workers rise above their long run average. While the data do not permit us to

distinguish quits from layoffs, this pattern is consistent with the workforce composition of firms becoming less skilled in the periods leading up to displacement.

Further results from our quantile regression analysis reveal significant changes to the distribution of worker quality in separation flows prior to displacement. In particular, the distribution of worker quality has a higher variance in the periods leading up to displacement. Relative to the distribution of separations from non-distressed firms, high-skill workers are more prevalent up to three periods before displacement. We view this as evidence in support of workers “abandoning the sinking ship.” In contrast, low-skill workers represent increasingly large fractions of flows between the year before displacement and the quarter immediately preceding the event. Again, these findings are roughly consistent with our working hypothesis. Finally, consistent with signaling models of worker quality (Gibbons and Katz 1991), we find that at the time of displacement workers at all points in the skill distribution of movers are of higher quality than their counterparts in the distribution for non-distressed firms.

Of course, a few caveats apply. In particular, the decomposition of job and worker flows is relative to firm specific averages of these variables. The quantile analysis, however, is relative to the global distribution of worker quality in worker separations. This may explain why the distribution of worker quality is left-shifted in the two periods immediately preceding displacement, whereas separation rates for high skill workers are above average. The tremendous heterogeneity in workplace practices may also contribute to this discrepancy (see for instance, Haltiwanger, Lane, and Spletzer (2000)) and a subject of further analysis. The picture we draw is also incomplete because of our focus on separations. Future consideration of the distribution of worker quality in hires as well as other post-displacement outcomes may prove to be equally as interesting and important.

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Table 1: Person summary statistics

Variable	All	High-tenure
Dummy, 1=male 0=female	0.52 (0.49)	0.51 (0.49)
Dummy, 1=white 0=non-white	0.70 (0.45)	0.77 (0.41)
Total Number of Observations / Person	21.74 (19.41)	46.66 (12.95)
Total Number of Employers	3.87 (4.06)	3.29 (2.67)
Total Number of Quarters Worked	19.08 (16.32)	42.22 (7.18)
Displacement event (>30%)	0.12 (0.32)	0.14 (0.35)
Number of individuals	4,539,451	866,009

Standard deviation in parentheses.

Table 2: Overall sample means

Variable	All	High-tenure
Firmsize	1592.93 (3347.24)	2341.89 (4069.09)
Age	35.34 (12.11)	39.75 (10.88)
Incremental Experience	15.93 (12.53)	21.17 (13.10)
Dummy, 1=male 0=female	0.51 (0.49)	0.51 (0.49)
Dummy, 1=white 0=non-white	0.72 (0.44)	0.76 (0.42)
Tenure (Quarters)	9.39 (10.37)	16.17 (12.51)
Real Quarterly Earnings (\$1997)	6290.39 (7099.26)	8523.70 (7912.00)
Displacement event (>30%)	0.04 (0.19)	0.02 (0.15)
Sample size	98,726,271	40,416,160
Number of individuals	4,539,451	866,009

Standard deviation in parentheses.

Table 3: Firms reducing employment by more than 30 percent, 1985-1997

Mean employment (sample)	Fraction estabs displaced	Avg. times displacement	Fraction estabs displaced (alt)	Avg. times displacement (alt)
$25 < EMP \leq 200$	0.718154	1.468463	0.634446	1.024409
$200 < EMP \leq 1000$	0.690037	1.346863	0.583553	0.872957
$1000 < EMP$	0.623418	1.151899	0.471519	0.632911

Table 4: Firm deaths

Mean employment (sample)	Fraction estabs displaced	Avg. times displacement	Fraction estabs displaced (alt)	Avg. times displacement (alt)
$25 < EMP \leq 200$	0.518779	0.518779	0.497624	0.497624
$200 < EMP \leq 1000$	0.489721	0.489721	0.472852	0.472852
$1000 < EMP$	0.389241	0.389241	0.373418	0.373418

Figure 1: Effect at different percentiles (i)

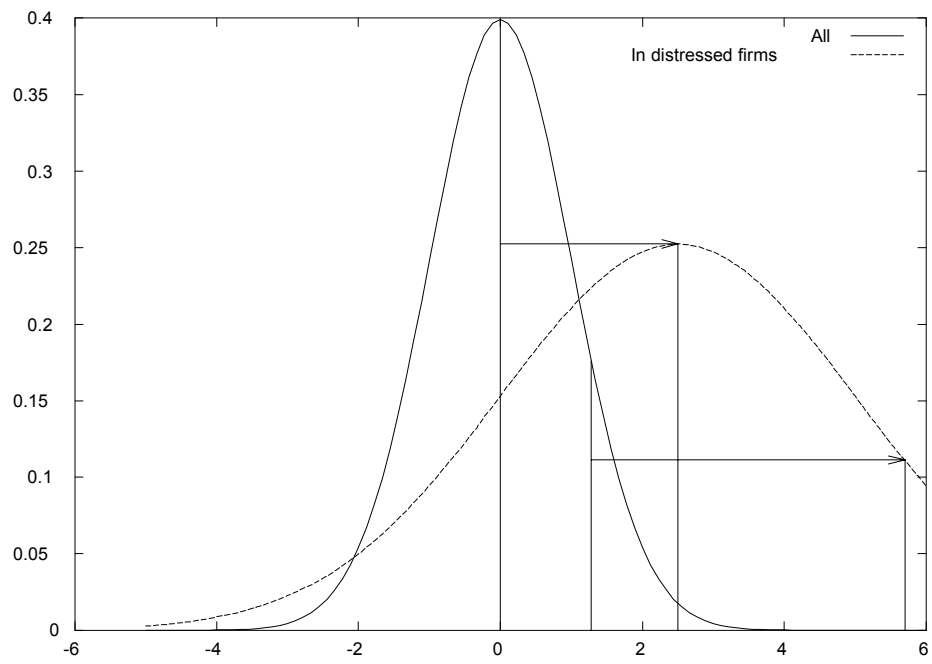


Figure 2: Effect at different percentiles (ii)

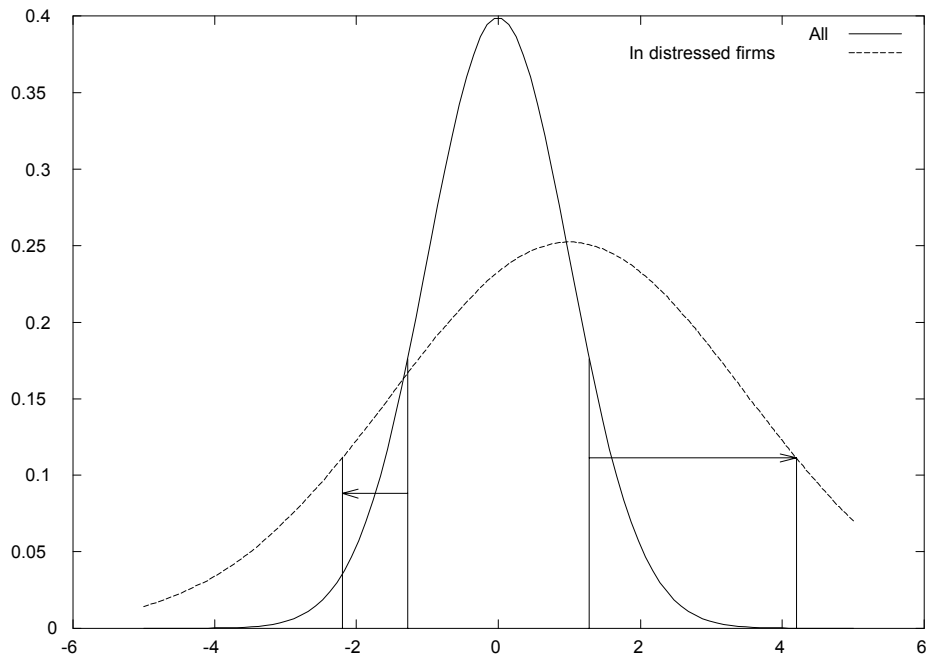


Figure 3: Effect at given values

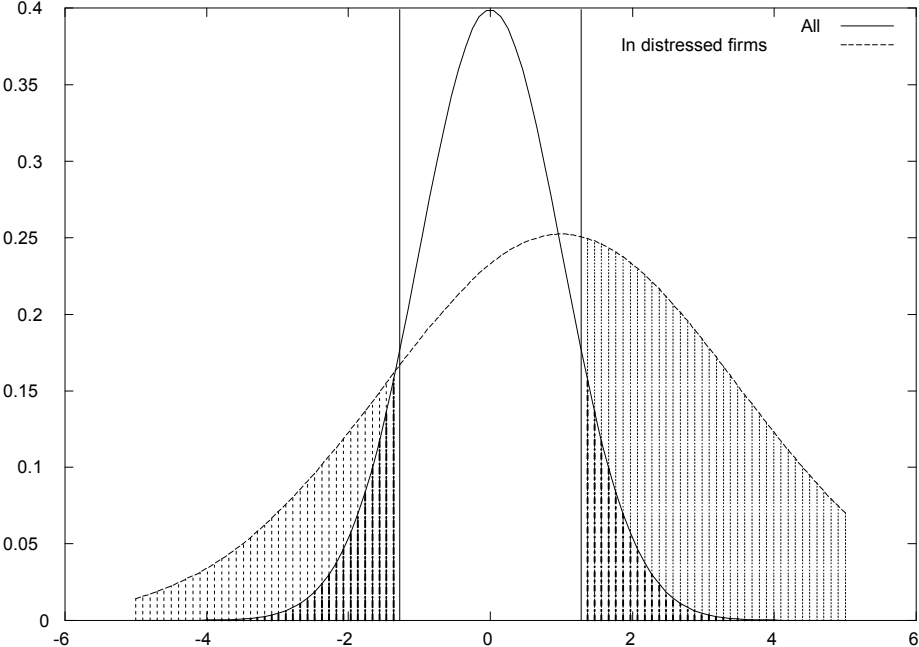


Figure 4: Preliminary results: Earnings regressions

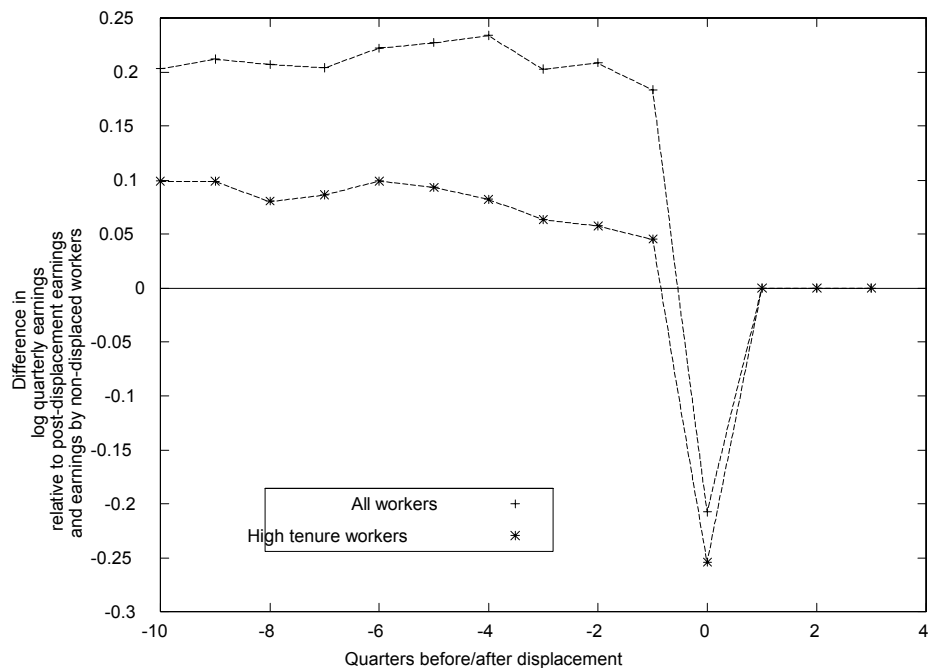


Figure 5: Preliminary results: Jobflow, accession, separation, and churning rates

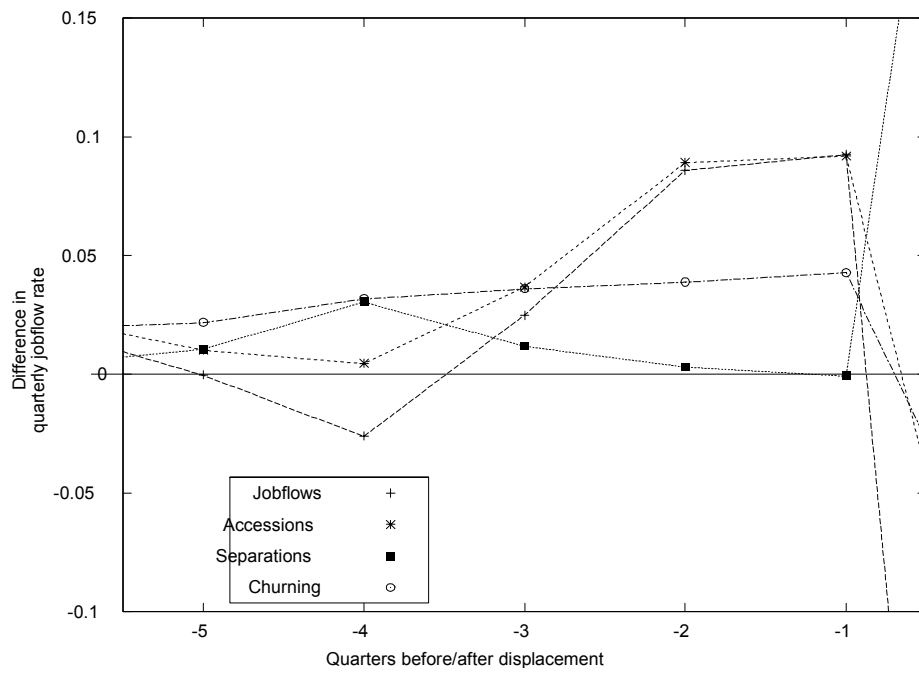


Figure 6: Preliminary results: Jobflows by skill group

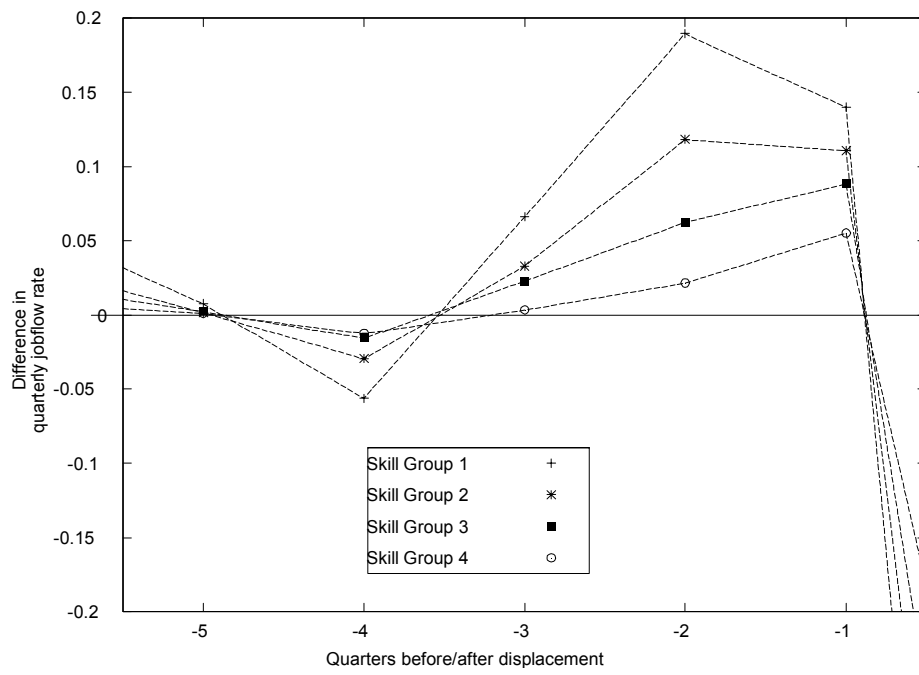


Figure 7: Preliminary results: Accessions by skill group

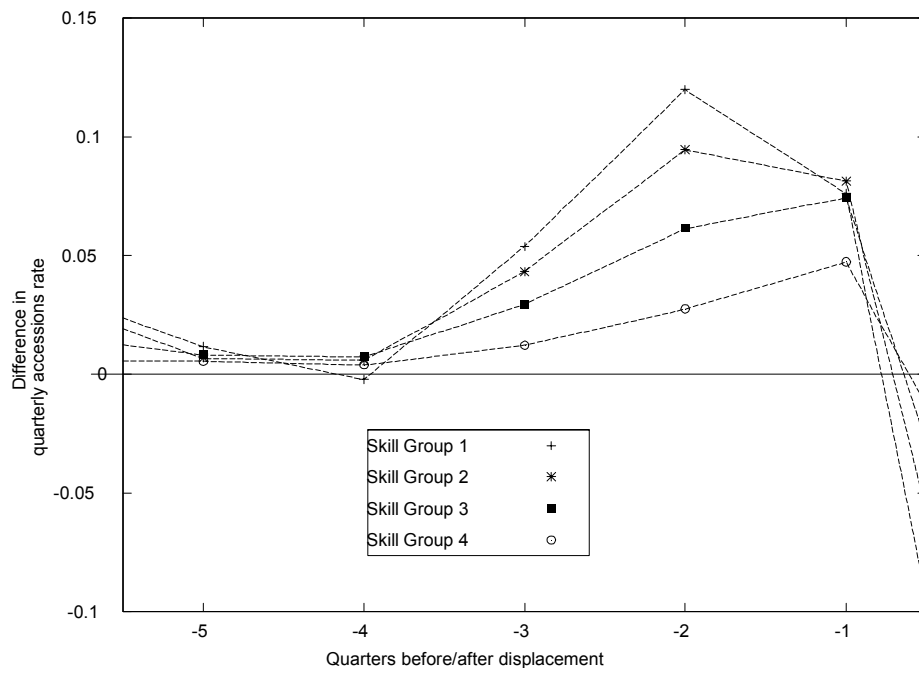


Figure 8: Preliminary results: Separations by skill group

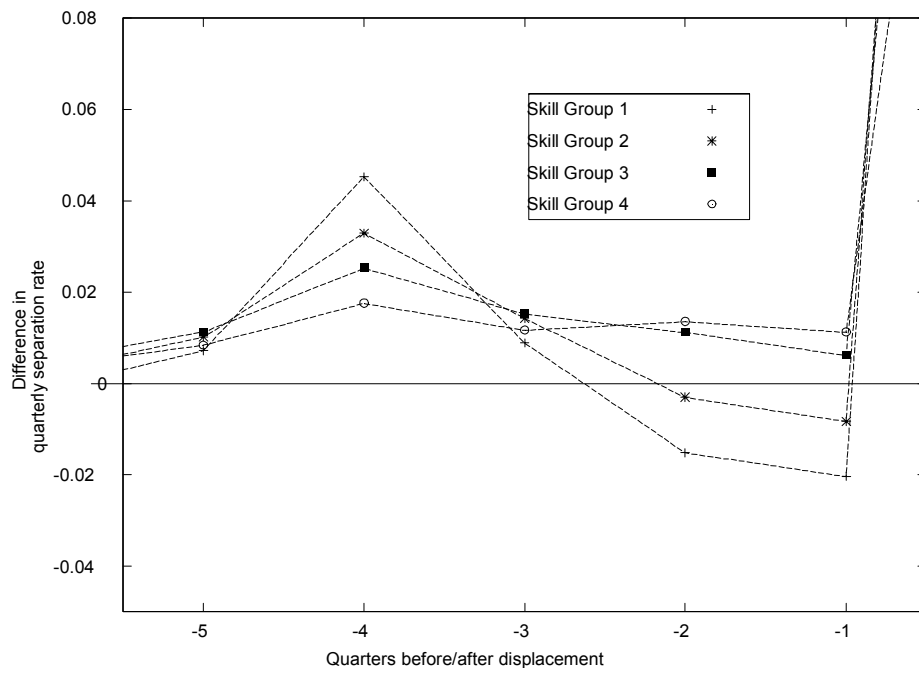


Figure 9: Preliminary results: Churning rates by skill group

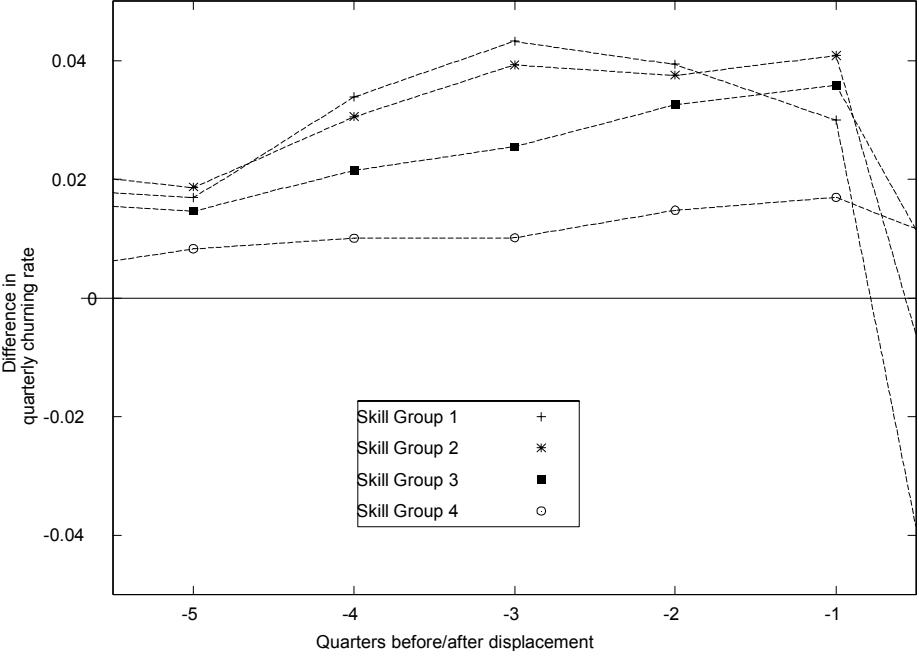
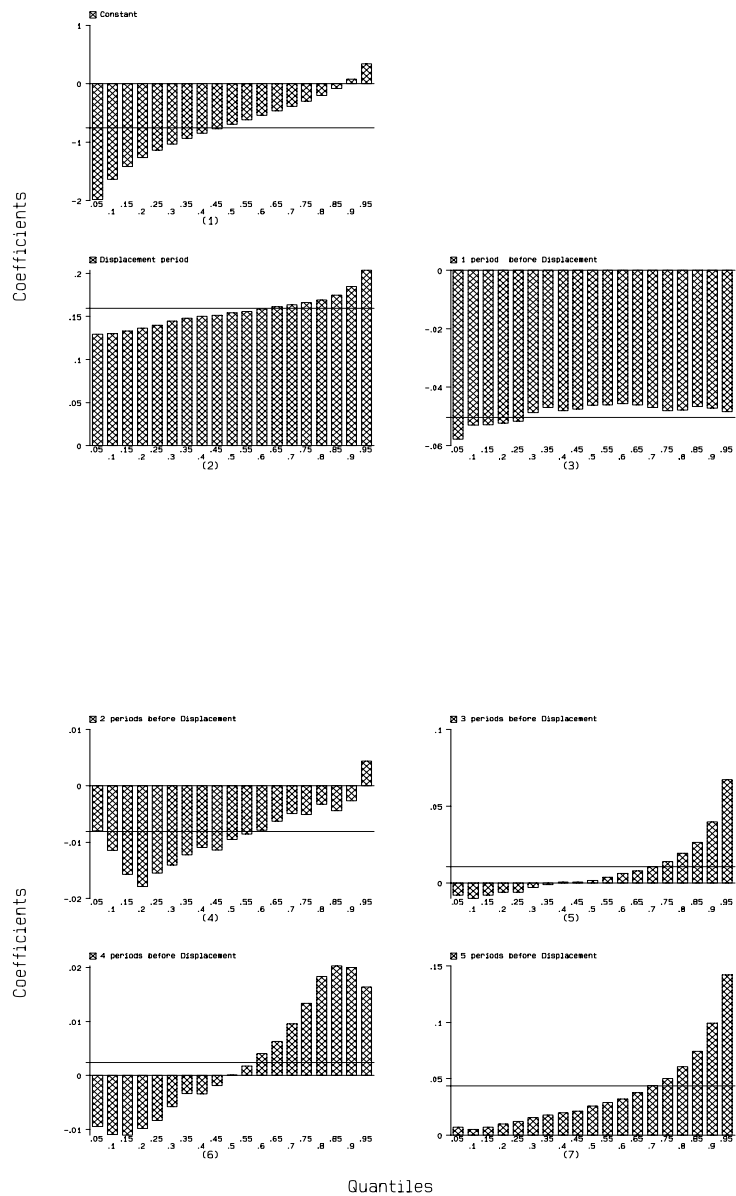
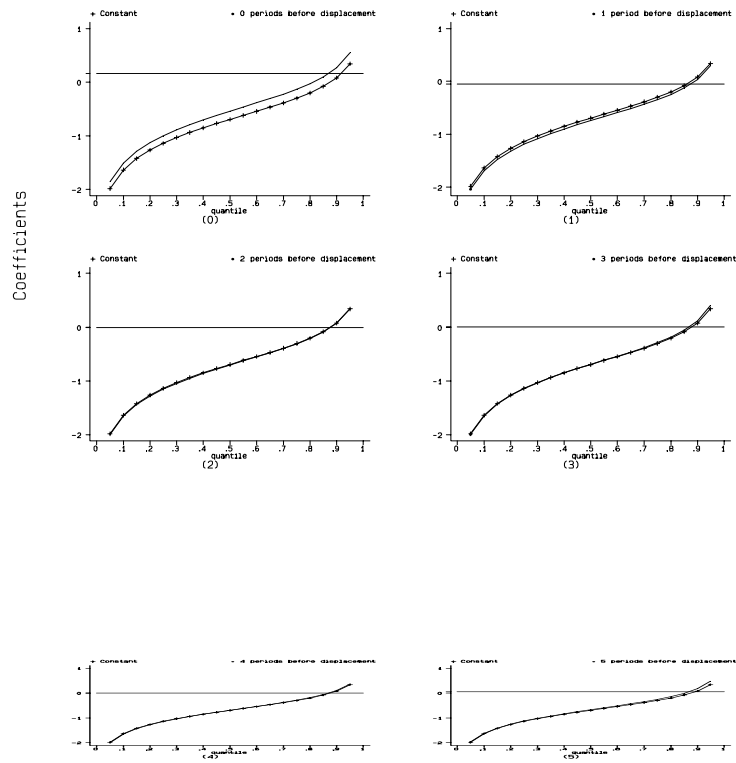


Figure 10: Preliminary results: Change in worker quality quantiles (i)



(30 percent displacement, raw employment, 50% file)

Figure 11: Preliminary results: Change in worker quality quantiles (ii)



(30 percent displacement, raw employment, 50% file), cumulation