Using linked employer-employee data to investigate the speed of adjustment in downsizing firms

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Abstract

When firms are faced with a demand shock, adjustment can take many forms. Firms can adjust physical capital, human capital, or both. The speed of adjustment may differ as well: costs of adjustment, the type of shock, the legal and economic enviroment all matter. In this paper, we focus on firms that downsized between 1992 and 1997, but ultimately survive, and investigate how the human capital distribution within a firm influences the speed of adjustment, *ceteris paribus*. In other words, when do firms use mass layoffs instead of attrition to adjust the level of employment.

We combine worker-level wage records and measures of human capital with firm-level characteristics of the production function, and use levels and changes in these variables to characterize the choice of adjustment method and speed. Firms are described/compared up to 9 years prior to death. We also consider how workers fare after leaving downsizing firms, and analyze if observed differences in post-separation outcomes of workers provide clues to the choice of adjustment speed.

1 Introduction

The U.S. labor market is a very dynamic environment; gross firm-level job creation and destruction dominate job growth. Worker flows are three to four times higher than net job flows at the firm level, and high levels of "churning" (worker flows in excess of job flows) are a persistent characteristic of firm personnel policy (Burgess et al., 2000a). High levels of churning (Burgess et al., 2000b) and large layoffs (Abowd et al., 2005a) are correlated with a lower probability of survival and lower future employment growth (Burgess et al., 2000a).

One limitation is that most of the literature's focus has been on fairly short-term employment variations. In this paper, we focus on firms that experience large employment reductions within a defined period of time, and investigate the speed with which this reduction occurs. In particular, we are interested in what firm and workforce characteristics are associated with choosing a very rapid employment reduction - a mass layoff - over a more gradual adjustment process.

While our discussion will be couched primarily within the context of choosing to use mass layoffs instead of a gradual employment adjustment, this study also contributes to the larger literature on labor force adjustment, and in particular the speed of labor force adjustment if adjustment occurs.

Factors affecting the speed of labor force adjustment, or the determinants of dynamic labor demand, have been studied extensively (see Hamermesh (1986), for an overview). Determinants are generally some variation on hiring and firing costs, but also include the level of firm-specific human capital (Neal, 1995; Parent, 2000), management of effects on morale (Armstrong-Stassen, 1993; Brockner, 1990; Konovsky and Brockner, 1993), etc. Often, the precise components of those adjustment costs are not measurable. While the literature has identified and measured some margins along which labor demand is adjusted in repsonse to shocks, most prominently hours, we will not be able to measure most of them here. Where this paper will contribute is to identify and measure the human capital distribution in the firm. Furthermore, since the virtual universe of employers is represented in our sample, relatively homogeneous subgroups of firms can be formed in order to adequately control for many of the other unmeasured determinants of adjustment speed.

In this paper, we focus on firms that ultimately survive, but are observed to have significant employment declines, and investigate the choice of adjustment speed. A companion paper (Abowd et al., 2005a) focuses on the correlates of firm closures. In both cases, we pay particular attention to the impact that levels and distributions of human capital within the firm, as well as changes therein, have on the outcome variables. We

- characterize medium-term outcomes of firms that experience a significant drop in employment, but ultimately survive
- consider the differentiated impact on worker outcomes (average earnings later)
- industry variation in these outcomes

We differ from the literature in our use of a measure of human capital, rather than a direct measure of wages, and we consider the effect of the distribution of human capital within a firm on the choice of the employment adjustment speed.

The paper is organized as follows. Section 3 lays out the basic definitions of human capital, slow decline and displacement as used in our paper. Section 4 describes the data used, and Section 5 provides (preliminary) results. Section 6 concludes.

2 Prior results

There is a broad literature on the flows of workers, and linking it to the lifecycle of the firm (see among others Burgess et al., 2000a,b; Davis et al., 1996). While the initial literature, exemplified by Davis et al. (1996), investigated flows between firms, the subsequent literature started looking within the black box of the firm (Abowd et al., 1999; Burgess et al., 2000a,b). Some authors have looked at detailed worker flows in relationship to job flows across different segments of the economy (Burgess et al., 2000b), and found significant intra-firm persistence of particular flow pattern. Abowd et al. (1999) consider workforce reductions, and Lengermann and Vilhuber (2002) consider the timeframe surrounding displacement events, but no research to our knowledge puts both of these groups into the same analytical framework. Relative to their respective comparison groups, firms in France that reduce employment do so primarily by reducing their inflows (Abowd et al., 1999), but firms in the United States that ultimately displace have increased volatility (churning) in both inflows and outflows, but also changes in the skill distribution within these flows (Lengermann and Vilhuber, 2002). In particular, the composition of outflows shifts to higher skilled workers. In general, firms with high levels of worker turnover ("churning") have lower probability of survival Burgess et al. (2000b) and lower future employment growth Burgess et al. (2000a), relative to other firms. Thus, it is interesting to consider the counter-factual: what about stable firms that have high net outflows, where churning may or may not be present. How do churning measures differ between these firms?

In our analysis, we focus on firms that have significant employment declines, but do ultimately survive. In this, we differ from a the literature that has focussed on plant closures, and often equated a plant closure as a mass layoff event. Mass layoffs, however, are not synonymous with the death of an establishment or firm. In Abowd et al. (2005a), 55 percent of firms that have one displacement event between 1993 and 1996 are still alive in 1997. Conversely, a gradual decline may result in the death of the firm without ever generating a mass layoff. Dunne and Roberts (1990), Bernard and Jensen (2002), and Carneiro and Portugal (2003) consider the determinants of wages and the effects on plant closures (Bernard and Jensen, 2002; Dunne and Roberts, 1990) or firm closures (Carneiro and Portugal, 2003). Dunne and Roberts (1990) find that higher-paying firms have a significant, but economically small increase in the likelihood of plant failure. One postulated explanation for this small effect is that plants with higher wages also have a more productive workforce. In contrast to Dunne and Roberts (1990), Bernard and Jensen (2002) found that plants paying above-average wages have a lower likelihood of exiting. One plausible explanation for this result is that these firms use above-average human capital.

Our analysis contributes to answering these questions in three different ways. For one, we use a measure of general (non-firm-specific) human capital instead of, or in addition to, wages and observable characteristics of the workforce. This turns out to be an important determinant of mass layoffs, similar to what Abowd et al. (2005a) found. Second, by focussing on firms that survive, rather than firms that exit the market, we can provide an additional element of the overall picture that has been neglected in the past. Finally, we link mass layoffs and general workforce adjustments together, and incorporate a link to the literature on flows by including flow measures as correlates of the decision to use mass layoffs.

3 Definitions

The definitions of "human capital"and "mass layoff" are obviously crucial for our analysis. In this section we consider each concept, in turn, state our definition and relate our measure to alternatives that have been used by others.

Defining human capital

We provide a brief overview of our approach in this section. For a more complete discussion of the definition of the within-firm human capital distribution, and of human capital itself, see Abowd et al. (2002b). Assume human capital H_{it} has a market-return (average rental rate) r_t. The wage is $w_{it} = r_t H_{it}$, where i indexes persons and t indexes time. Individual firms might deviate from r_t, paying $r_t p_j$, with $E[p_j] = 1$, where j indexes employers. Assume that a person-specific component (θ_i) and a general experience component ($X_{it}\beta$) are important factors determining the accumulation of human capital. Then, taking logarithms, we have $\ln H_{it} = \theta_i + X_{it}\beta$. We thus obtain the following model of earnings

$$\ln w_{it} = \ln r_t + \psi_j + \theta_i + X_{it}\beta \tag{1}$$

where $\psi_j = \ln p_j$. Deviating w_{it} and X_{it} from the grand mean across individual and time periods produces the estimating equation:[1]

$$\ln w_{it} = \theta_i + \psi_j + X_{it}\beta + \epsilon_{ijt} \tag{2}$$

where θ_i is the person effect, ψ_j is the firm effect, and X_{it} are time-varying person characteristics, such as experience, and ϵ_{ijt} is the statistical residual.

[1]See Abowd et al. (2002a) for details. We have not changed the notation for the wage rate or the experience variables since subtracting a constant is just a technique for imposing one of the identification requirements for the estimation of both person and firm effects.

To compute a measure of a person's human capital, we combine the estimated person effect $\hat{\theta}_i$, the experience components (after restoring the mean of X_{it}) of person characteristics $X_{it}\hat{\beta}$, and the reference constant δ to compute

$$\hat{h}_{it} = \hat{\theta}_i + X_{it}\hat{\beta} + \delta \tag{3}$$

Because the estimated person effect $\left(\hat{\theta}_i\right)$ absorbs all the usual time-invariant explanatory factors, such as sex, education, and age at first entry, and also absorbs all unobserved (by the analyst) time-invariant factors, such as innate ability, h_{it} corresponds to the concept of "general human capital."

Once $\hat{h}_{it}$ is computed, we estimate firm-level kernel density estimates of its distribution, yielding a firm-specific distribution of human capital $g_{jt}(\hat{h}_{it})$, and

$$G_{jt}(\hat{h}) = \int_{\underline{H}}^{\hat{h}} g_{jt}(x)dx \tag{4}$$

where $\underline{H}$ and $\overline{H}$ define the support of $\hat{h}$. To obtain discrete measures, we partition $[\underline{H}, \overline{H}]$ into 4 subsets, and calculate the boundaries of the population quartiles q_k^* implicitly defined by

$$G(q_k^*) = \int_{\underline{H}}^{q_k^*} g(x)dx = k \cdot 0.25 \tag{5}$$

for $k = 0, 1, 2, 3, 4$. For each firm, we then calculate the proportion of workers who have human capital within the ranges defined by the overall population quartile boundaries q_k^* for $k = 1, 2, 3, 4$.

$$\Gamma_{jt}(k) = G_{jt}(q_k^*) - G_{jt}(q_{k-1}^*) \tag{6}$$

These employer-level measures summarize the complete distribution of workers' human capital at the establishment. Similar measures $\Gamma(k)$ are computed for the experience ($X_{it}\hat{\beta}$) and estimated person effect ($\hat{\theta}_i$) distributions within the firm.

While our firm-level human capital measure is obviously related to wage rates, it is important to note that it differs from the distribution of wages at the firm. By removing the firm effects and the idiosyncratic residuals from the wage, between-firm differences, which might be due to specific human capital or other active compensation policies, are no longer present in our human capital measure. Generally, such effects are included in within-firm wage dispersion measures used by other authors (e.g. Gibbons et al., 2005; Lluis, 2005).

Defining mass layoffs

Define the following measures (Abowd et al., 2005b): B_{jt} is firm j's beginning-of-quarter employment, a point-in-time measure derived by summing over workers employed at firm j in both period $t-1$ and t. M_{jt} is the raw count of workers who ever worked at firm j in quarter t. $B_j^{max} = \max_t B_{jq}$ is the maximum employment of firm j over the time period that firm j is in the sample with positive employment. S_{jt} are worker separations from firm j; *i.e.*, workers that worked for the firm in period t but are no longer observed on the payroll in period $t+1$, and equivalently accessions A_{jt}.

Similar to the previous literature on the impact on workers of mass layoffs (Bowlus and Vilhuber, 2002; Jacobson et al., 1993a,b; Schoeni and Dardia, 1996), we define a mass layoff in period t to occur when separations surpass 30% of firm j's maximum employment level over the observed time period. This event, and the period t_{ML} in which it occurs, are defined by

$$D_{jt_{ML}} = 1 \text{ if } \frac{S_{jt_{ML}}}{B_j^{max}} > 0.3 \tag{7}$$

Due to some limitations of the administrative data used for this paper, a naïve use of the mass layoff equation above will overstate mass layoffs by some margin.[2] In order to reduce the impact of "spurious" events, we take particular care to exclude firms that either change identity or who continue to operate, yet fail to file a firm report.

The firm identifier underlying all of our analysis is a state-specific Unemployment Insurance account number, whose primary purpose is to facilitate the administration of a state's unemployment insurance system. These account numbers can and do change for reasons such as a simple change in legal form or merger. In our analysis, the separation of a worker from a firm is identified by a change in the firm identifier on that worker's wage records. If a firm changes account numbers, but makes no other changes, the worker would seem to have left the original firm, when in fact his employment status remains unchanged. Thus, a simple change in account numbers would lead to the observation of a mass layoff at the firm associated with the original account number.[3]

To identify spurious employer birth and death events, we track large worker movements between firms. Benedetto et al. (2003) provide an analysis for one particular state of such an exercise using LEHD data. For this paper, if we observe 80% of a firm (the predecessor) moving to a single successor, then we eliminate the displacement event. . The assumption is that such a movement is associated not with a layoff, but a reorganization, a takeover, or some similar event. Similarly, if we observe that 80% of a successor's employment stems from the same predecessor, then a displacement event is also eliminated. Finally, firms linked in such a manner are treated as if they were a single firm. For instance, if firm A is alive in 1992, has an event as just described in Q1 of 1995, with successor firm B being identified, and the successor firm B is alive in 1997, then we

[2] Abowd and Kramarz (1999); Vilhuber (2004) provides an overview over several approaches to correcting the weaknesses of administrative datasets. Abowd and Vilhuber (2005) discuss one particular weakness, a corrective measure, and the impact it has on aggregate statistics, including on measures similar to the mass layoffs of interest in our paper.

[3] Other authors working with administrative data have also addressed this problem in similar ways, see Anderson and Meyer (1994) and Jacobson et al. (1993a).

treat the combined data from firms A and B as the single unit of analysis.[4]

Other notation

Now consider net job flows between two time periods $JF_{j,t_1}^{t_2} = B_{jt_2} - B_{jt_1}$. Corresponding job reallocation is $JR_{j,t_1}^{t_2} = \left|JF_{j,t_1}^{t_2}\right|$. Obviously, total worker flows over the time period are

$$WF_{j,t_1}^{t_2} = \sum_{t=t_1}^{t_2-1} \left(S_{jt} + A_{jt}\right), \tag{8}$$

and excess turnover, or churning (Burgess et al., 2000a)) is the amount of worker flows that exceeds the minimal necessary worker flows to achieve net job flows:

$$CF_{j,t_1}^{t_2} = WF_{j,t_1}^{t_2} - JR_{j,t_1}^{t_2} \tag{9}$$

To compute rates WFR and CFR, respectively, we divide by the average employment over the period.

Business variables (sales, capital intensity, Herfindahl index) are only defined in 1992 and 1997, and we denote changes in these variables simply as ΔX, where X represents the relevant variable.

4 Data

The LEHD Infrastructure Files provide longitudinal information about workers, firms and the match between them, thus allowing us to calculate displacement events as well as the distribution of human capital. To estimate the impact of displacement, we use the LEHD Infrastructure Files from three states, California, Illinois, and Maryland, covering the time period 1990-2003 (Abowd et al., 2005b). The files contain each worker's quarterly earnings history, basic demographic information, and, most importantly, a person's employer.

We focus our analysis on survivors – firms with positive employment in both 1992 and 1997 – that experienced a 30% drop in employment sometime between 1992 and 1997. Firms that meet this criterion may have periods of inactivity, but new entrants (firms not alive in 1992, but active in 1997) and exiters (firms active in 1992, but not alive in 1997) are excluded. This sample differs from Abowd et al. (2005a), where exiters were also included, and from Abowd et al. (2002b), where both exiters and new entrants were included.

[4] In this preliminary version of the paper, due to the unavailability of the LEHD Successor-Predecessor File for California in the RDC network, California was excluded from such processing. The final paper will contain symmetric processing for all states.

More formally, we select firms that experienced a decline in employment during the time period of at least 30% of their maximum employment. If for each firm j, there exists a t_{max} defined by $B_{jt_{max}} = \max_t[B_{jt}]$, then the sample selection criterion for each firm can be stated as:

$$-JF^{t^*}_{j,t_{max}} \geq 0.3B_{jt_{\max}}; t^* > t_{max} \tag{10}$$

Thus, by t^*, firms have suffered at least a 30% decline in employment. Some firms may have suffered that employment decline much quicker than others. In particular, we will distinguish firms that reduce employment very quickly, within one quarter, through displacement as defined in Equation (10).

For both groups, we are interested in how their employment evolves relative to the period where the firm has reached a 30% decline in employment or the period where the displacement occurs. Thus, both t^* and t_{ML} may not end the employment decline and the firm's behavior before and after the adjustment period is worth further exploration. Define equivalently to $B_{jt_{max}}$ the lowest level of employment over the time period, $B_{jt_{min}} = \min_t[B_{jt}]$, where t_{min} may or may not be the same as t^*. For some parts of the analysis, we compute measures of job growth (decline) and churning prior to t_{min}, and after t_{min}, in both cases excluding the actual t_{min} quarter.[5]

Due to the dynamic nature of the U.S. economy it is difficult to differentiate "normal" flows of employment from displacements for smaller firms. For example, under our standard definition a firm with 10 employees that has 3 workers leave during the quarter would be classified as having a displacement, even though this is not a particularly unusual event. In order to focus our analysis on "large" displacement events, we further limit our sample to firms that have at least 50 workers at the start of the sample period, 1993 quarter 2. This group of firms make-up the core of the sample we analyze in this paper.

Quarterly firm employment and payroll histories are available from the LEHD infrastructure files, along with additional information such as size, industry, and location (Abowd et al., 2005b).[6] However, data on a firm's sales and capital stock is gathered from the 1992 and 1997 Economic Censuses, and linked through the (preliminary version of the) LEHD Business Register Bridge. This additional information adds to the richness of our data, but unfortunately the capital stock is available only for the manufacturing sector, while sales is available only for a subset of firms. At the time we were preparing this version, the 2002 Economic Census has not been fully processed, although we expect to use these data in the future.

The human capital estimates defined by Equation (2) were acquired from LEHD's Human Capital Estimates File, last calculated for 22 states available as of November 30, 2004. To get a snapshot or point-in-time measure of the human capital at the firm, we restrict our analysis to workers employed at the end of quarter 1 in 1992 and 1997, a date that roughly coincides with the collection of Economic Census data. Firm-level distributions are computed for all workers between the ages of 18 and 70, with earnings during the quarter of greater than $250.00.

[5] Strictly speaking, we define t_{min} as the *first* time that the minimum is achieved.

[6] The coverage within a state is exceptionally broad. Typically 98% of all employment is found in covered firms.

5 Analysis

Our sample selection process begins with 48,455 firms located in California, Illinois, and Maryland that are alive in 1992, of which 39,418 survive until 1997. Of the 39,418 surviving firms, 8,152 experience either a displacement event or a 30% decline in employment sometime between 1992 and 1997. We then exclude firms that are missing key information such as industry or firm size and also exclude agriculture and public sector firms due to the incomplete coverage of the QCEW in these two sectors, resulting in a final analysis sample of 5,441 firms.

Table 1 provides an overview of our three main analysis groups in 1992; slow decliners, single displacers, and multiple displacers. In summary, the single displacers and slow decliners are relatively similar, but the multiple displacers differ substantially between the former two groups. Relative to the slow decliners, single displacers are more prevalent in: construction; transportation, communications, and utilities; and retail, while the multiple displacers are heavily concentrated in construction, retail, and services. The single displacers, on average, have larger employment (422) than the slow decliners (339), with the multiple displacers far behind (252). The observable worker characteristics are surprisingly similar between slow decliners and single displacers, with virtually the same average age, proportion white, and proportion male. Multiple displacement firms tend to have younger, part time workers relative to firms in the other two groups.

The average log earnings are somewhat different for the single displacers and slow decliners, with an about 8 percent gap, but average earnings are over 50% less for the multiple displacers. Given the multiple displacement events, a large portion of the earnings gap for the latter group likely represents a substantial difference in labor force attachment, rather than a pure wage gap. The human capital measures adjust for labor force attachment differences, and this is reflected in the distributions of human capital we present further down in Table 1. The mean of each wage component is presented along with the proportion of a firm's workers that lie between fixed cutoff points in the overall distribution.[7]

Slow decliners are more skilled overall, but the differences are not as large as the gap in average earnings, especially for multiple displacers. The employees of firms in the slow decliners category have a slightly lower h, which is almost exclusively due to a lower distribution of θ, although the differences are not very large. The multiple displacers have lower human capital overall, with the gap divided almost equally between experience and θ. Interestingly, slow declining firms pay relatively high wages (ψ) compared to single displacers and especially multiple displacers that pay especially poor wages conditional on the quality of their workforce.

The final part of Table 1 presents additional firm characteristics such as the capital stock per worker, and sales per worker. Single displacer firms tend to be larger, have more capital per worker, yet have slightly lower worker productivity. This result is interesting when combined

[7]The quartile reference points are based on the 1992 distribution of human capital in the 22 states used to produce the human capital estimates. Therefore, a firm with 25% of it's employees in each quartile would have the same human capital distribution as the overall workforce

with the distribution of human capital at the firm. Sales per worker does appear to be positively correlated with human capital, a result we would expect *a priori*.

In Table 2 we assemble a picture of how our three groups evolved between 1992 and 1997. Not surprisingly given our grouping strategy, the slow displacers take the longest time ($t_{min} - t_{max}$) to reach their employment minimum followed by the single and then multi displacers. All three groups have a large decline in employment between 1992 and 1997, but the single displacers show the largest decline of approximately 68% (percent employment growth in B).

In addition to the overall employment change, we also explore the employment dynamics both before and after minimum employment. The 8-quarter pre- and post growth variables are calculated 8 quarters before and 8 quarters after, respectively, the quarter of minimum employment between 1992 and 1997, t_{min}. Once again all three groups show substantial declines in employment, with single displacers having the largest decline of about 50%.[8] The three groups also have substantial amounts of churning (per Equation 9) and a relatively high worker flow rate (per Equation 8) before and after the minimum. Once again the single displacers have higher churning and worker flow rates than the slow decliners, but in this case, not surprisingly given their classification, the multiple displacers have the highest of all. However, after minimum employment is reached, the single and multiple displacers begin to grow, while the slow decliners continue to reduce their employment. At this point it is unclear whether the lack of employment growth represents different demand shocks faced by the two groups, or possibly an inability of the slow decliners to recover as quickly from productivity shocks.

The last section in Table 2 shows the change in human capital over the period for each group. The slow decliners and single displacers have a similar pattern of upskilling for h and experience, but the slow decliners have a larger relative increase in experience and show mild upskilling for θ with no increase in the upper quartile. This implies a different transformation of the workforce over the period. The slow decliners appear to be dramatically increasing the proportion of their workforce with high experience (high firm specific human capital), while the single displacers appear to be increasing the proportion of their workforce with more general human capital (especially in the upper quartile). It is unclear whether this difference is due to some sort of workforce adjustment restrictions imposed on the slow decliners, but the single displacers appear to be more successfully increasing their skill level. Multiple displacers have the smallest increase in h, with relatively small increases in experience and a decline in θ.

Tables 4 through 11 report results from a series of probits that model the choice between a one period displacement and a multi period employment reduction. In order to provide a connection to the previous literature, which has often focused on the manufacturing sector, the first set of results (Tables 4-7) report are for the manufacturing sector only. Subsequent tables expand the scope of the analysis to all sectors (excluding agriculture, mining, and public administration), eliminating firms

[8]The minimum employment quarter itself is excluded from our calculations, however for single displacers the minimum employment quarter is not always coincident with the displacement event. Due to the impact of a displacement on our comparisons, we will specifically break out this event in future revisions.

that did not report sales, but dropping the capital intensity variable from the analysis (Tables 9-10). Table 11 report results for the full sample, but does not include either capital intensity or labor productivity measures. Finally, Tables 12 and 13 replicate the analysis of Tables 9 and 10, but eliminates firms that experienced multiple displacement events. Within each set of results, a number of specification checks are performed, since not all variables are available for all firms. All results control for, but do no report coefficients for the date of t_{min}, whether a firm had a business presence in other states, and state.

In manufacturing, the more capital intensive (prop_acs) firms have a slight tendency to prefer faster layoffs. This is robust to the inclusion of many further controls, including measures of worker flow and churning. A possible explanation maybe that the cost of a misallocation of workers is higher for these firms, or that the specific human capital is lower given the higher (absolute, not relative) capital intensity. As other authors have found, firms with multiple establishment (multi_unit) more easily resort to displacement, possibly because they have available expertise at other plants or can shift "surviving" workers from the failed plant to another part of the company. However, contrary to previous results, in this particular sample, firm size is not correlated with the choice of displacement. Interestingly, the market structure within a firm's local two-digit SIC industry (as measured by the 2-digit SIC Herfindahl index, herf_2) does not affect the choice. Note that labor productivity never plays a role when entered into the analysis.

Among the human capital variables, when controlling for capital intensity, the fraction of workers in the lowest quartile of the human capital distribution $\Gamma(1)$ is significantly and positively related to the likelihood of the firm choosing displacement over more gradual employment adjustment. Interestingly, this result is consistent with findings in Abowd et al. (2005a), which uses the same database, but reports findings for a much broader sample of firms, including firms that report growth throughout most of the period and firms that shut down. Most other observable characteristics of the workforce do not affect the choice of the firm, except for the racial distribution of the workforce when not controlling for human capital. We will contrast this with the results for the broader samples in the next sections.

Tables 9-10 report results for a sample of firms that reported sales. Remarkably, given the absence of labor productivity in the determination of the speed of adjustment in manufacturing, is the strong negative effect in this sample (Table 9). The effect of $\Gamma(1)$, however, is quite similar: having an above fraction of workers from the lower end of the human capital distribution increases the speed of layoffs. Note that $\Gamma(2)$ now also has a significant, but opposite effect. Also different from both the manufacturing sector is the strong effect of average observable characteristics of the workforce (gender, race, experience), despite controlling for the overall human capital distribution. Also in contrast to the results from the manufacturing sector is the effect of firm size, which here demonstrates a positive correlation with displacements: larger firms are more likely to displace than small firms. On the other hand, having multiple establishments has no effect. Further analysis needs to investigate whether this is due to strong changes in the presence of multi-establishment firms across industries. Table 10 tests a specification for this same sample, dropping the sales variable, without much of an impact on any of the other coefficients, and only a very small change in the log likelihood. Table 11 uses the same specification as Table 10, expanding the analysis to all firms, whether or not they report capital measures or sales. The general pattern is again very similar to the previous set of results.

The sample still contains a signficant number of firms that experience multiple displacements, and in other work (Abowd et al., 2005a), we have eliminated these firms due to the signficant differences in the overall pattern of flows and firm-level observables between multiple displacers and other firms. The results in Table 13 are for a sub-sample that excludes the multiple displacers. Again, the results are broadly similar, although less precisely estimated.

6 Conclusion

Empirical research into the effects of "shocks" on a firm's labor force typically suffers from an identification problem: how to actually identify the shock. The analysis in this paper attempts to circumvent the problem by focussing on a select group of firms that have all been observed to have acted or reacted to some major event: they have reduced their workforces by a significant amount (over 30 percent) within a fairly short period of time (on average 3 years). Furthermore, to cast the workforce reduction as a measure designed not to close down a firm, but to result in a "saved" firm, we select firms that ex-post survive the shock. Some of these firms have decided to reduce their workforces much more rapidly than others: through a mass layoff. Although the incidence of the shock is arguably homogeneous across this group of firms, the magnitude may still be different.

Nevertheless, classifying firms by whether or not they used a mass layoff to reduce their workforce reveals some remarkable similarities, providing support for our approach, and some differences in observable characteristics of these firms before they achieve the lowest point. For instance, despite these characteristics not being part of the sampling strategy, the firms are very similar in many of the observable characteristics of their workforces. They differ in their use of capital and by the measured labor productivity, as well as in the average quality of the unobservables of their workforce. Firms that do not displace pay higher wages, but also have a more qualified workforce, on average, and pay higher salaries for a given quality of worker. As the probability models reveal, these differences stand out, even when controlling for all other variables.

This research complements previous work on the correlates of displacements, by focussing on a select set of firms: firms that ultimately survive, and yet have had to perform significant adjustments of their workforce.

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7 Tables

Table 1: Means for full sample

	Slow decline		Mass layoff		Multiple mass layoffs	
	Mean	Std.	Mean	Std.	Mean	Std.
SIC C	0.025	0.156	0.049	0.216	0.122	0.327
SIC D	0.351	0.477	0.292	0.454	0.118	0.322
SIC E	0.045	0.208	0.065	0.247	0.038	0.191
SIC F	0.113	0.317	0.112	0.316	0.046	0.210
SIC G	0.075	0.263	0.104	0.305	0.264	0.441
SIC H	0.118	0.323	0.096	0.296	0.043	0.204
SIC I	0.270	0.444	0.279	0.449	0.366	0.482
Employment 1993:2	339.339	1267.64	421.685	1265.74	251.631	508.147
White (firm mean)	0.645	0.223	0.661	0.216	0.637	0.230
Male (firm mean)	0.559	0.220	0.571	0.228	0.564	0.249
Age (firm mean)	37.232	3.758	37.273	4.020	34.942	5.158
Fulltime (firm mean)	0.954	0.051	0.944	0.061	0.877	0.101
Log real wage (firm mean)	10.334	0.484	10.248	0.532	9.669	0.708
ψ (firm mean)	0.167	0.239	0.133	0.259	-0.164	0.368
h (firm mean)	9.875	0.263	9.859	0.275	9.716	0.304
$\Gamma_h(1)$	0.238	0.154	0.244	0.161	0.335	0.181
$\Gamma_h(2)$	0.249	0.075	0.247	0.077	0.247	0.075
$\Gamma_h(4)$	0.267	0.151	0.259	0.153	0.205	0.158
$X\hat{\beta}$ (firm mean)	0.801	0.069	0.801	0.074	0.743	0.116
$\Gamma_{X\hat{\beta}}(1)$	0.242	0.113	0.245	0.118	0.333	0.178
$\Gamma_{X\hat{\beta}}(2)$	0.313	0.049	0.308	0.049	0.283	0.063
$\Gamma_{X\hat{\beta}}(4)$	0.293	0.092	0.296	0.096	0.258	0.109
θ (firm mean)	0.113	0.246	0.097	0.256	0.012	0.260
$\Gamma_\theta(1)$	0.249	0.156	0.253	0.162	0.304	0.163
$\Gamma_\theta(2)$	0.247	0.075	0.245	0.075	0.246	0.072
$\Gamma_\theta(4)$	0.264	0.152	0.255	0.150	0.218	0.145
Capital stock/ worker	71.905	113.888	111.292	178.616	71.822	96.989
Sales / worker	395.126	2648.09	348.112	1516.95	131.024	408.895
N	1756		1423		2262	

Table 2: Flow and human capital measures

	Slow decline		Mass layoff		Multiple mass layoffs	
	Mean	Std.	Mean	Std.	Mean	Std.
$t_{min} - t_{max}$	12.656	4.480	10.007	5.254	9.517	4.994
Pct Employment growth (B) Overall period	-0.430	0.353	-0.681	0.624	-0.480	0.580
Pct Employment growth (B) PRE 8 period (alt)	-0.323	0.286	-0.500	0.650	-0.348	0.568
Pct Employment growth (B) POST 8 period	-0.026	0.468	0.156	0.704	0.113	0.675
Churning in PRE 8 period	277.812	1581.90	449.197	1401.66	1317.33	4783.14
Churning in POST 8 period	318.174	2202.84	363.096	917.929	876.237	1895.72
Worker flow rate in PRE 8 period	1.459	0.729	2.124	1.171	5.628	4.162
Worker flow rate in POST 8 period	1.939	1.672	3.861	26.753	8.644	44.340
$\Delta\Gamma_h(1)$	-0.056	0.072	-0.053	0.110	-0.031	0.101
$\Delta\Gamma_h(2)$	-0.000	0.055	-0.008	0.080	0.002	0.065
$\Delta\Gamma_h(4)$	0.028	0.078	0.047	0.148	0.017	0.102
$\Delta\Gamma_{X\beta}(1)$	-0.093	0.076	-0.075	0.088	-0.064	0.092
$\Delta\Gamma_{X\beta}(2)$	-0.003	0.062	-0.001	0.071	0.006	0.062
$\Delta\Gamma_{X\beta}(4)$	0.060	0.060	0.050	0.083	0.038	0.066
$\Delta\Gamma_{\theta}(1)$	-0.016	0.071	-0.023	0.113	0.005	0.102
$\Delta\Gamma_{\theta}(2)$	0.009	0.045	0.002	0.077	0.008	0.060
$\Delta\Gamma_{\theta}(4)$	-0.003	0.075	0.020	0.146	-0.011	0.101

Variable definitions

Table 3: Explanation of variable names

labor_prod2	Labor productivity
prop_acs	Capital intensity
exper_Mean	Firm avg. experience
male_Mean	Proportion of men
white_Mean	Proportion white
age_Mean	Firm avg. age
h_pct0to25	$\Gamma(1)$
h_pct25to50	$\Gamma(2)$
h_pct75to100	$\Gamma(4)$
herf_2	Herfindahl SIC2
multi_unit	Firm has multiple sites
lemp_start	Employment at start of period

Manufacturing

Table 4: demographics, No H, capital, laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	1.5957	0.7515	0.1228	3.0687	4.51	0.0337
labor_prod2	1	-0.0020	0.0739	-0.1468	0.1428	0.00	0.9786
prop_acs	1	0.0942	0.0455	0.0050	0.1833	4.29	0.0384
exper_Mean	1	-1.8704	1.4824	-4.7758	1.0349	1.59	0.2070
male_Mean	1	0.0074	0.2703	-0.5224	0.5371	0.00	0.9782
white_Mean	1	-0.3933	0.2377	-0.8592	0.0725	2.74	0.0979
age_Mean	1	0.0035	0.0217	-0.0391	0.0460	0.03	0.8735
herf_2	1	-0.6185	0.7101	-2.0102	0.7732	0.76	0.3837
multi_unit	1	0.2853	0.1289	0.0326	0.5380	4.90	0.0269
lemp_start	1	0.0192	0.0558	-0.0902	0.1286	0.12	0.7305
Log Likelihood			-547.5142673				
Number of Observations Used				819			

Table 5: No demographics, H, capital, laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.5140	0.7053	-1.8963	0.8683	0.53	0.4662
labor_prod2	1	0.0501	0.0766	-0.1000	0.2002	0.43	0.5131
prop_acs	1	0.1050	0.0449	0.0170	0.1930	5.47	0.0193
h_pct0to25	1	0.9616	0.5240	-0.0654	1.9886	3.37	0.0665
h_pct25to50	1	0.1326	0.9955	-1.8185	2.0836	0.02	0.8941
h_pct75to100	1	-0.1868	0.8225	-1.7988	1.4253	0.05	0.8204
herf_2	1	-0.6056	0.7089	-1.9950	0.7837	0.73	0.3929
multi_unit	1	0.2735	0.1284	0.0219	0.5251	4.54	0.0332
lemp_start	1	0.0070	0.0547	-0.1002	0.1142	0.02	0.8985
Log Likelihood			-545.7982393				
Number of Observations Used				819			

Table 6: demographics, H, capital, laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.3816	1.3048	-2.9389	2.1758	0.09	0.7700
labor_prod2	1	0.0543	0.0773	-0.0972	0.2059	0.49	0.4824
prop_acs	1	0.1014	0.0459	0.0115	0.1914	4.89	0.0270
exper_Mean	1	-0.7211	1.5267	-3.7134	2.2713	0.22	0.6367
male_Mean	1	0.4986	0.3503	-0.1880	1.1853	2.03	0.1546
white_Mean	1	-0.0082	0.2847	-0.5662	0.5497	0.00	0.9769
age_Mean	1	-0.0036	0.0223	-0.0474	0.0401	0.03	0.8710
h_pct0to25	1	1.3463	0.7441	-0.1121	2.8046	3.27	0.0704
h_pct25to50	1	0.1295	1.0573	-1.9428	2.2018	0.01	0.9025
h_pct75to100	1	0.0558	0.8870	-1.6827	1.7944	0.00	0.9498
herf_2	1	-0.6413	0.7139	-2.0406	0.7580	0.81	0.3691
multi_unit	1	0.2806	0.1295	0.0269	0.5344	4.70	0.0302
lemp_start	1	0.0284	0.0560	-0.0813	0.1382	0.26	0.6116

Log Likelihood -544.0842143

Number of Observations Used 819

Table 7: demographics, H, no capital, laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.6369	1.2964	-3.1778	1.9040	0.24	0.6232
labor_prod2	1	0.1138	0.0724	-0.0281	0.2558	2.47	0.1160
exper_Mean	1	-0.5941	1.5156	-3.5645	2.3764	0.15	0.6951
male_Mean	1	0.6177	0.3465	-0.0614	1.2968	3.18	0.0746
white_Mean	1	0.0555	0.2827	-0.4986	0.6097	0.04	0.8443
age_Mean	1	-0.0013	0.0222	-0.0449	0.0422	0.00	0.9517
h_pct0to25	1	1.2882	0.7436	-0.1691	2.7456	3.00	0.0832
h_pct25to50	1	0.0562	1.0560	-2.0137	2.1260	0.00	0.9576
h_pct75to100	1	0.0774	0.8861	-1.6593	1.8141	0.01	0.9304
herf_2	1	-0.8332	0.7112	-2.2272	0.5608	1.37	0.2414
multi_unit	1	0.2894	0.1293	0.0360	0.5428	5.01	0.0252
lemp_start	1	0.0451	0.0554	-0.0635	0.1536	0.66	0.4158

Log Likelihood -546.5447687

Number of Observations Used 819

Table 8: demographics, H, no capital, no laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.0804	1.2506	-2.5315	2.3707	0.00	0.9487
exper_Mean	1	-0.4802	1.5212	-3.4617	2.5014	0.10	0.7523
male_Mean	1	0.5995	0.3460	-0.0787	1.2778	3.00	0.0832
white_Mean	1	0.0434	0.2822	-0.5098	0.5966	0.02	0.8778
age_Mean	1	-0.0033	0.0222	-0.0467	0.0401	0.02	0.8816
h_pct0to25	1	1.0339	0.7250	-0.3871	2.4548	2.03	0.1539
h_pct25to50	1	-0.0596	1.0537	-2.1248	2.0057	0.00	0.9549
h_pct75to100	1	0.0855	0.8860	-1.6510	1.8220	0.01	0.9231
herf_2	1	-0.8825	0.7098	-2.2737	0.5087	1.55	0.2137
multi_unit	1	0.3076	0.1288	0.0553	0.5600	5.71	0.0169
lemp_start	1	0.0584	0.0547	-0.0488	0.1656	1.14	0.2857

Log Likelihood -547.7811916

Number of Observations Used 819

All industries, firms reporting sales

Table 9: demographics, H, no capital, laborProd

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Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	0.9214	0.5450	-0.1468	1.9896	2.86	0.0909
labor_prod2	1	-0.0998	0.0288	-0.1562	-0.0434	12.03	0.0005
exper_Mean	1	-1.4888	0.6630	-2.7883	-0.1894	5.04	0.0247
male_Mean	1	0.8442	0.1393	0.5712	1.1173	36.72	<.0001
white_Mean	1	0.3106	0.1309	0.0541	0.5671	5.63	0.0176
age_Mean	1	-0.0021	0.0112	-0.0241	0.0199	0.04	0.8514
h_pct0to25	1	1.3439	0.3427	0.6722	2.0155	15.38	<.0001
h_pct25to50	1	-1.0248	0.5918	-2.1848	0.1351	3.00	0.0833
h_pct75to100	1	-0.5295	0.4319	-1.3760	0.3170	1.50	0.2202
herf_2	1	-0.2358	0.4778	-1.1722	0.7006	0.24	0.6216
sicc	1	1.1394	0.1186	0.9070	1.3719	92.32	<.0001
sice	1	0.4587	0.1165	0.2304	0.6869	15.51	<.0001
sicf	1	0.2021	0.0965	0.0130	0.3913	4.39	0.0362
sicg	1	0.5858	0.0902	0.4091	0.7626	42.21	<.0001
sich	1	0.1393	0.0976	-0.0521	0.3307	2.03	0.1538
sici	1	0.3542	0.0758	0.2056	0.5028	21.82	<.0001
multi_unit	1	-0.0498	0.0564	-0.1604	0.0608	0.78	0.3776
lemp_start	1	0.1138	0.0270	0.0608	0.1668	17.72	<.0001
Log Likelihood			-2064.191914				
Number of Observations Used				3736			

Table 10: demographics, H, no capital, no laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	0.4745	0.5285	-0.5613	1.5103	0.81	0.3693
exper_Mean	1	-1.5841	0.6614	-2.8803	-0.2878	5.74	0.0166
male_Mean	1	0.9007	0.1380	0.6301	1.1712	42.57	<.0001
white_Mean	1	0.3157	0.1306	0.0597	0.5717	5.84	0.0156
age_Mean	1	-0.0010	0.0112	-0.0229	0.0210	0.01	0.9311
h_pct0to25	1	1.5533	0.3367	0.8933	2.2132	21.28	<.0001
h_pct25to50	1	-1.0334	0.5905	-2.1907	0.1239	3.06	0.0801
h_pct75to100	1	-0.6963	0.4283	-1.5357	0.1431	2.64	0.1040
herf_2	1	-0.3609	0.4762	-1.2942	0.5723	0.57	0.4484
sicc	1	1.1518	0.1184	0.9197	1.3838	94.62	<.0001
sice	1	0.4948	0.1158	0.2679	0.7217	18.26	<.0001
sicf	1	0.0792	0.0898	-0.0967	0.2551	0.78	0.3775
sicg	1	0.5952	0.0901	0.4185	0.7718	43.60	<.0001
sich	1	0.1342	0.0976	-0.0570	0.3254	1.89	0.1689
sici	1	0.4285	0.0726	0.2862	0.5708	34.83	<.0001
multi_unit	1	-0.0572	0.0563	-0.1676	0.0532	1.03	0.3098
lemp_start	1	0.1066	0.0269	0.0539	0.1593	15.71	<.0001
Log Likelihood			-2070.218085				
Number of Observations Used				3736			

All industries, all firms

Table 11: demographics, H, no capital, no laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	0.0284	0.4354	-0.8251	0.8818	0.00	0.9481
exper_Mean	1	-0.9866	0.5320	-2.0294	0.0562	3.44	0.0637
male_Mean	1	0.9002	0.1125	0.6796	1.1207	64.01	<.0001
white_Mean	1	0.3277	0.1092	0.1136	0.5418	9.00	0.0027
age_Mean	1	-0.0028	0.0090	-0.0204	0.0148	0.10	0.7563
h_pct0to25	1	1.7776	0.2753	1.2380	2.3172	41.69	<.0001
h_pct25to50	1	-1.1831	0.4800	-2.1240	-0.2423	6.07	0.0137
h_pct75to100	1	-0.5156	0.3392	-1.1804	0.1493	2.31	0.1285
sicc	1	1.1288	0.0986	0.9356	1.3221	131.07	<.0001
sice	1	0.5059	0.0978	0.3142	0.6975	26.76	<.0001
sicf	1	0.1311	0.0724	-0.0107	0.2730	3.28	0.0700
sicg	1	0.6851	0.0766	0.5349	0.8353	79.90	<.0001
sich	1	0.1859	0.0788	0.0315	0.3403	5.57	0.0183
sici	1	0.5183	0.0581	0.4045	0.6321	79.68	<.0001
multi_unit	1	-0.0654	0.0470	-0.1575	0.0268	1.93	0.1645
lemp_start	1	0.1021	0.0224	0.0583	0.1460	20.87	<.0001

Log Likelihood -3045.801233

Number of Observations Used 5441

All industries, firms reporing sales, no multiple displacements

Table 12: demographics, H, no capital, laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.8910	0.7049	-2.2727	0.4907	1.60	0.2063
labor_prod2	1	0.0554	0.0356	-0.0144	0.1251	2.42	0.1198
exper_Mean	1	-0.3470	0.8712	-2.0544	1.3605	0.16	0.6904
male_Mean	1	0.3256	0.1807	-0.0285	0.6798	3.25	0.0715
white_Mean	1	0.3342	0.1639	0.0130	0.6554	4.16	0.0414
age_Mean	1	0.0008	0.0137	-0.0261	0.0276	0.00	0.9562
h_pct0to25	1	0.6956	0.4244	-0.1363	1.5274	2.69	0.1013
h_pct25to50	1	-0.3946	0.7126	-1.7913	1.0020	0.31	0.5797
h_pct75to100	1	-0.4468	0.5145	-1.4551	0.5616	0.75	0.3852
sicc	1	0.5922	0.1565	0.2856	0.8989	14.33	0.0002
sice	1	0.3386	0.1340	0.0761	0.6012	6.39	0.0115
sicf	1	0.0394	0.1104	-0.1770	0.2558	0.13	0.7212
sicg	1	0.1917	0.1135	-0.0308	0.4142	2.85	0.0913
sich	1	0.0018	0.1153	-0.2242	0.2278	0.00	0.9873
sici	1	0.1474	0.0938	-0.0363	0.3312	2.47	0.1159
multi_unit	1	0.0037	0.0674	-0.1284	0.1359	0.00	0.9558
lemp_start	1	0.1240	0.0315	0.0623	0.1858	15.52	<.0001
Log Likelihood			-1456.37893				
Number of Observations Used			2184				

Table 13: demographics, H, no capital, no laborProd

Parameter	DF	Estimate	Error	Limits		Square	Pr > ChiSq
Intercept	1	-0.6255	0.6835	-1.9652	0.7141	0.84	0.3601
exper_Mean	1	-0.2988	0.8706	-2.0052	1.4076	0.12	0.7315
male_Mean	1	0.2973	0.1798	-0.0550	0.6497	2.74	0.0981
white_Mean	1	0.3255	0.1637	0.0045	0.6464	3.95	0.0469
age_Mean	1	-0.0001	0.0137	-0.0269	0.0268	0.00	0.9966
h_pct0to25	1	0.5783	0.4174	-0.2399	1.3965	1.92	0.1659
h_pct25to50	1	-0.3925	0.7126	-1.7891	1.0040	0.30	0.5817
h_pct75to100	1	-0.3714	0.5120	-1.3749	0.6320	0.53	0.4682
sicc	1	0.5892	0.1564	0.2826	0.8958	14.18	0.0002
sice	1	0.3214	0.1335	0.0597	0.5831	5.79	0.0161
sicf	1	0.1116	0.1001	-0.0846	0.3077	1.24	0.2649
sicg	1	0.1918	0.1135	-0.0307	0.4142	2.86	0.0911
sich	1	0.0118	0.1150	-0.2136	0.2373	0.01	0.9183
sici	1	0.1153	0.0915	-0.0639	0.2946	1.59	0.2074
multi_unit	1	0.0049	0.0674	-0.1272	0.1370	0.01	0.9424
lemp_start	1	0.1280	0.0314	0.0665	0.1895	16.64	<.0001
Log Likelihood			-1457.590609				
Number of Observations Used				2184			