Employment Adjustment Costs and Establishment Characteristics

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CES 99-15

* This paper is a revised version of a chapter from my Ph.D. dissertation at the University of Maryland. I would like to thank my committee members, Timothy Dunne, Curt Grimm, John Haltiwanger, Edward Montgomery, and Plutarchos Sakellaris, and seminar participants at the Census Bureau’s Center for Economic Studies for their helpful comments. I would also like to thank Ricardo Caballero, Eduardo Engel, and John Haltiwanger for allowing me to use their employment data set. Research results and conclusions expressed are those of the author and have not been endorsed by the Census Bureau.

ABSTRACT

Microeconomic employment adjustment costs affect not only employment adjustments at the micro level but may also profoundly impact aggregate employment dynamics. This paper sheds light on the nature of these microeconomic employment adjustment costs and quantifies their impact on aggregate employment dynamics. The empirical exercises in the paper analyze the differences in employment adjustments by establishment characteristics within a hazard model framework using micro data for approximately 10,000 U.S. manufacturing plants. I find that employment adjustments vary systematically by establishment characteristics; moreover, these variations suggest that employment adjustment costs reflect the technology of the plant, the skill of its workforce, and the plant's access to capital markets. Concerning the structure of the adjustment costs, the employment adjustments have significant nonlinearities and asymmetries consistent with nonconvex, asymmetric adjustment costs. Specifically, employment adjustment behavior shows substantial inertia in the face of large employment surpluses, varied adjustment behavior for small deviations from desired employment, and (S,s)-type of bimodal adjustments in response to large employment shortages. Finally, the micro level heterogeneity, asymmetries, and nonlinearities significantly impact sectoral and aggregate employment dynamics.

Keywords: Labor Demand, Adjustment Costs, Panel Data.

JEL Classification: C33, J23, J32.

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"The vast literature on dynamic factor demand has been organized around the concept of costs of adjustment. The standard assumption has been that these costs are convex and symmetric... [This] convenient approximation detracts from our ability to provide useful discussions of macroeconomic behavior and microeconomic policies... An important first step will therefore be to discover the correlates of the structures of adjustment costs in order to learn how widespread each potential [structure] of these costs is... Discovering the size of adjustment costs and how these too vary by industries' and workers' characteristics should be high on anyone's research agenda in the study of factor demand."

Hamermesh and Pfann (1996, p. 1289)

1. Introduction

Microeconomic employment adjustment costs affect not only employment adjustments at the micro level but may also profoundly impact aggregate employment dynamics. At the beginning of their extensive review of the current state of research concerning factor demand adjustment costs, Hamermesh and Pfann (1996) set forth four questions that need to be answered about adjustment costs. The questions concern the *source*, *size*, and *structure* of the adjustment costs facing an individual agent and the *macroeconomic* implications of these adjustment costs. Since it has proven difficult to directly observe and measure employment adjustment costs, this paper addresses these questions indirectly by examining differences in employment adjustments over worker and plant characteristics. Specifically, this paper examines establishment-level employment adjustments within a hazard framework for approximately 10,000 U.S. manufacturing plants over a variety of worker and plant characteristics. In addition to shedding light on the source, size, and structure of the micro adjustment costs, this paper quantifies the impact of these costs on sectoral and aggregate employment dynamics.

There are many sources of employment adjustment costs.[1] There are explicit adjustment costs such as the costs of contracted-out advertising, testing, processing, and training new workers when expanding the workforce and costs related to legal requirements and regulations when reducing the workforce. Other costs are less explicit such as the adjustment costs that arise from restructuring the workforce (including planning and organizational costs) and those associated with changing the mix of inputs. For employment increases that require expansions across other dimensions (for example, acquiring more equipment), these adjustment costs can include the costs of obtaining access to financial capital. Finally, there are implicit employment adjustment costs which represent the loss of productivity that ensues as work shifts from producing output to absorbing employment changes. Thus there are many potential *sources* of adjustment costs, the few direct measurements of the *size* of employment adjustment costs suggest that they are significant.[2]

Much of the recent literature on dynamic factor demand centers on a debate concerning the *structure* of adjustment costs. The structure of adjustment costs affects not only the nature of the micro-level

[1] As this paper focuses on adjustment costs in terms of the labor demand decision, changes in employment that reflect job matching or life cycle issues are not as relevant, and hence net employment changes are studied rather than gross employment changes.

[2] See Oi (1962) and Nickell (1986) for examples of *directly* measuring employment adjustment costs. Concerning *indirect* identification of the sources and size of employment adjustment costs, see Foster (1999) which uses the more traditional partial adjustment model as a theoretical framework.

adjustments but can also determine the nature of the aggregate dynamics in response to shocks. Specifically, the relevant features of the adjustment cost function are its symmetry and convexity. Concerning symmetry, there is no reason to suppose that adjustment costs are of the same magnitude over the expansion and contraction sides of employment adjustments. The issue of convexity concerns whether the employment adjustment cost function has two components: costs that vary over the size of the adjustment and costs that are fixed over the size of the adjustment. The structure of adjustment costs has implications for the smoothness of adjustments to a shock. Unlike convex adjustment costs which are associated with smooth, continuous adjustments to shocks, these fixed adjustment costs are associated with lumpy adjustments.

The existing literature on employment adjustment costs using micro-level data suggests that adjustment costs are asymmetric and nonconvex. Within the employment adjustment asymmetry literature, however, there is no consensus as to which side has the greater adjustment costs.[3] Studies that use establishment-level data report evidence consistent with nonconvex adjustment costs. Hamermesh (1989, 1992a) finds that a model that allows for nonconvexities in adjustment costs dominates the

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[3] Pfann and Verspagen (1989) and Schiantarelli and Sembenelli (1993) find evidence suggesting that the adjustment costs are higher on the hiring side. However, Jaramillo, Schiantarelli, and Sembenelli (1993) find evidence that the adjustment costs are higher on the firing side. The relatively small samples used in these studies for a select number of industries makes drawing general conclusions difficult. In addition, there may be differences across countries that account for the variation in the results. Caballero, Engel, and Haltiwanger (1997) find evidence consistent with adjustment costs that are higher on the firing side. In a study using aggregate data, Palm and Pfann (1993) find that hiring costs exceed firing costs for production workers but that the reverse is true for nonproduction workers. Chang and Stefanou (1988) reject symmetry of adjustment costs. Holzer and Montgomery (1990) do not find evidence of an asymmetric adjustment pattern for employment until they analyze large and small firms separately. They find that large firms adjust more in reaction to negative shocks, while small firms adjust more in reaction to positive shocks.

quadratic adjustment cost model for two small sets of micro data. In two related papers using Italian data, Rota (1997a, 1997b) finds that fixed adjustment costs are important, and moreover, concludes that employment decisions can be described by an (S,s) rule with symmetric bounds. Caballero, Engel, and Haltiwanger (1997) using a large dataset of U.S. manufacturing plants find that plants adjust disproportionately more to large (absolute) employment shortages and that establishment-level employment adjustments often are either non-existent or complete suggesting that employment adjustments can be characterized by an (S,s) model. This paper extends the work in Caballero, Engel, and Haltiwanger (1997) by broadening their framework to encompass plant-level heterogeneity in employment adjustment costs by worker and establishment characteristics.

Given the range of types of adjustment costs, it is reasonable to expect that adjustment costs might vary for different types of workers and plants. This introduction outlined four broad sources of adjustment costs: costs related to the skill of the workers, costs related to the plant technology, costs associated with access to capital markets, and institutional and regulatory costs of adjustment. The relative importance of these different adjustment costs may vary systematically by certain worker and establishment characteristics. For example, one might expect employment adjustment costs to be higher for more skilled workers. Estimates of the speed of adjustment parameter from the partial adjustment model suggest that differences in adjustment costs with respect to technology and worker skill are particularly important.[4] Furthermore, the structure of the adjustment cost function might vary with plant characteristics. Extending the example above, having found that adjustment costs are larger

[4] Foster (1999) finds faster speeds of adjustment for production workers and younger, smaller plants.

for more skilled workers, one may further discover that the employment adjustments suggest that fixed adjustment costs are especially important on the hiring side and less important on the firing side. Since directly measuring the adjustment costs is not feasible, employment adjustment costs are indirectly analyzed by examining differences in establishment-level employment adjustments taking into account differences in the establishments' age, average plant and firm size, ownership type, industry classification, shutdown technology, location, input intensities, and workforce skill level.

The adjustment hazards approach developed by Caballero and Engel (1993) serves as the theoretical framework for the empirical analysis in this paper. This framework enables one to determine whether adjustment costs are asymmetric and nonconvex and can be extended to allow for heterogeneity across workers and establishments. Furthermore, the adjustment hazard approach can establish whether the nonlinearities, asymmetries, and heterogeneity potentially uncovered at the micro plant-level are empirically significant at the sectoral and aggregate levels. Much of the existing literature on adjustment costs stresses the importance of using highly disaggregated data in empirical analysis.[5] The empirical analysis in this paper uses quarterly production worker employment data for approximately 10,000 U.S. manufacturing plants, and is thus well-suited to the task of analyzing micro employment adjustment costs as it is disaggregated spatially, temporally, and by worker type.

This paper is organized in the following manner. The hazard model is described in the next section. The data are described in the Section 3. Section 4 contains parametric analyses of employment adjustments. Section 5 examines the sectoral and aggregate dynamics when there are nonconvexities at

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[5] Hamermesh (1990, 1992b) stresses the importance of using spatially and temporally disaggregated data. Nickell (1984) notes the importance of using data disaggregated by worker type.

the micro level. Concluding remarks are presented in Section 6.

2. Theoretical Framework: State-Dependent Hazard Model

Average aggregate employment growth (Δ E) is decomposed into three pieces by Caballero and Engel (1993): it is the sum over all employment shortages (z) of the product of these shortages, the adjustment hazard function (A) and the distribution of deviations (f). That is,

(1) $$\Delta E_t \equiv \int z \; A(z,t)\, f(z,t)\, dz$$

The adjustment hazard function (A) determines the fraction of the employment deviation closed on average by plants with a particular deviation (z) at time t. The shape of this adjustment hazard function (A) is influenced by the structure of adjustment costs and, in turn, has a profound effect on plant-level and aggregate employment dynamics. The distribution of deviations (f) reflects the full range of employment shortages or surpluses that can exist at different plants at one time immediately following the latest idiosyncratic shocks. Shifts in this cross-sectional density of employment shortages evolve depending on the aggregate shock, the number of plants that adjust, and the idiosyncratic shocks. Similarly at the plant-level, employment changes reflect the hazard function and plant-level deviations in desired employment. That is,

(2) $$\Delta E_{et} = A(z_{et}) z_{et}$$

The basic building block for this decomposition is the deviation of actual employment from the employment that would be optimal in the *momentary* absence of any frictions (z). Specifically, the employment deviation (or shortage) is defined as:

$$z_{et} = n_{et}^{*} - n_{et-1} \tag{3}$$

Where n_{et} is the log of actual employment at establishment *e* at time *t* and n^*_{et} is the log of desired employment at establishment *e* at time *t*. Thus this gap measures the current employment shortage (z) which can arise due to both aggregate and idiosyncratic shocks. Caballero and Engel (1993) note that under certain conditions one can approximate this desired employment up to an additive constant by the solution to the static optimization problem. The relationship that results from this optimization relates the change in employment deviations (z) to the change in hours (h):

$$\Delta z_{et} = \theta \Delta h_{et} \tag{4}$$

Where θ is determined by the technology of the production function, the elasticity of wages with respect to hours, and the market structure.[6] Given how θ is defined, this parameter may vary over a number of plant characteristics.

To see why the shape of the hazard function is important it is useful to consider two examples, the constant hazard and the increasing hazard.[7] With a constant hazard function, plant-level employment adjustments are constant over the size of the employment shortage (z). The constant hazard is

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[6] This relationship is derived explicitly in Foster (1998). Specifically, $\theta=(\mu-\beta\gamma)/(1-\alpha\gamma)$. Where μ=elasticity of wages with respect to hours , β=output elasticity of hours, α=output elasticity of employment, and γ is a function of the price elasticity of demand.

[7] See Caballero, Engel, and Haltiwanger (1997) for a similar discussion and Foster (1998) for other examples, derivations of the employment dynamics, and a detailed discussion concerning the choice of functional forms for the state-dependent hazard.

consistent with convex adjustment costs as plants close some fraction of the employment gap in each period because too rapid adjustment yields higher and higher adjustment costs. The *plant-level* change in employment is a linear function of the employment deviations. Similarly, the *aggregate* employment dynamics in response to a contemporaneous aggregate shock are linear. This is because only the first moment of the cross-sectional distribution matters. To see this, imagine a shift in the cross-sectional distribution. In this case, the fraction of the gap that plants close remains the same, the only relevant thing that has changed is the average size of the employment deviation.[8]

Caballero and Engel (1993) prefer an increasing adjustment hazard as it has the intuitively appealing implication that plants do not tolerate large deviations from desired as much as they do small deviations.[9] The *plant-level* employment growth rate is still positively related to the deviation, but it is now more sensitive to large deviations than small. The *aggregate* employment dynamics for the increasing hazard model depend on the first and third moments of the cross-sectional distribution of moments. Any shift in the distribution towards the tails of the hazard function brings a more than proportional increase in the employment adjustments as the probability of adjusting has risen as well as the size of the adjustment (since the adjustments are full and the deviations are growing). This increasing adjustment hazard has the property that it is consistent at the *aggregate* level with the (S,s) model if there is heterogeneity of agents concerning the width of the band of inactivity.

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[8] At the aggregate level it is not possible to distinguish between having plants continuously adjusting 8 of the deviation (as in the partial adjustment model) from some fraction 8 of plants adjusting completely. However, it is possible to distinguish between these two different adjustment-types by looking at the empirical distribution of adjustment rates.

[9] The specific functional form they use is a second-order polynomial. A(z)= $8_0+8_2z^2$.

A. Plant Characteristics

The above discussion of the state-dependent hazard model implies that all plants have the same adjustment hazard function. However, one finding common to work using plant-level data is the tremendous heterogeneity of plants across many dimensions. Plant characteristics may affect employment adjustment costs and hence may affect the adjustment hazard. Plant characteristics that are likely to affect employment adjustment costs include general worker skill-level, plant technology, institutional and regulatory environment, and access to financial capital markets.

Starting with Oi's (1962) pioneering work, many researchers have found significant differences in employment adjustments over workers of different skill levels (measured here as production versus nonproduction workers).[10] Furthermore, nonproduction worker adjustments may be more costly as they may entail adjustments over other inputs, such as capital. Griliches (1969) and Bergstrom and Panas (1992) find evidence that skilled employment is more complementary with capital than is unskilled employment. Brown, Hamilton, and Medoff (1990) note that large firms (which tend to operate large establishments) are more likely to hire more educated, more experienced, older workers than small firms. One possible reason for this that they cite is that large firms may tend to be more capital intensive. Thus the literature suggests that more skilled workers face larger adjustment costs.

There are a variety of technological factors that can impact employment adjustment costs and hence the hazard function. Capital-intense establishments are likely to face high adjustment costs, as these

[10] See also Abraham and Houseman (1989) for a discussion about differences by worker types. See Dunne, Haltiwanger, and Troske (1997) for a discussion of using these worker types as measures of skill differences.

employment adjustments have a greater chance of involving an adjustment in the capital stock which itself faces high adjustment costs. Although adjusting energy may be relatively costless, the energy intensity of an establishment may reveal information about its technology. Since energy intensive plants tend to be also capital intensive, one might expect energy intensive establishments to have higher adjustment costs. The use of shift work can affect the ease with which a plant manager can adjust an establishment's employment to accommodate a large shock. Adjustment costs associated with planning and restructuring may be smaller for establishments that employ shifts.[11] Shift-work tends to be more associated with occupations found in the production worker group than the nonproduction worker group and to be more associated with industries that are capital-intensive.[12] Of course, the presence of shifts does not necessarily mean that it is feasible to adjust over shifts; many establishments that have shifts are also continuous operators which makes adjustment over shifts infeasible. Continuous processing establishments have large start-up and shut-down costs that make adjustments over employment relatively more expensive than for assembly-type producers who have small start-up and shut-down costs (see Mattey and Strongin (1994)). One would expect that large employment adjustments are most easily accomplished in establishments that have shifts and are also assembly-type producers. The age of the establishment can give information concerning the maximum vintage of the

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[11] Mayhsar and Solon (1993) find that "[w]hen full-time employment declines during a recession, about one-half of the decline for manufacturing production workers and one-third of the economy-wide decline occur on late shifts (p.227)."

[12] King and Williams (1985) note that the prevalence of a late-shift varies greatly among manufacturing industries, "ranging from less than 5 percent of the production workforce in such labor intensive industries as apparel ... to approximately one-half in more capital intensive industries such as cotton and manmade textiles..(p. 26)." Mellor (1986) finds that shift-work in manufacturing is most prevalent in primary metals, automobiles, paper products, chemicals, and rubber and plastics.

capital at the establishment, thus allowing for some comparison across establishments concerning technology. Berman, Bound, and Griliches (1994) found evidence of labor-saving technical change in the manufacturing sector over the latter part of the sample in this paper. During this period, nonproduction workers gained in relative importance at establishments. It may be that older establishments use older, more production-worker intensive technology. The size of the plant may also reveal information about its technology. Kandel and Pearson (1995) show that in theory larger establishments will tend to hire relatively more permanent workers *ceteris paribus*. Hence, increased establishment size may be associated with less flexibility and thus slower adjustment.

Institutional constraints to adjusting employment include union agreements and laws that constrain layoffs. The unionization of an establishment may increase its costs of adjusting or make adjustments over some margins impossible. There are legal constraints to layoffs on both the federal and state levels. In addition, the experience rating system of unemployment benefits, which differs by states, can produce costs of adjustments for those establishments that are below the threshold level. Many labor regulations exclude smaller firms and large firms are more likely to be unionized than small firms. While direct measures of these institutional constraints are not readily available, variation by industry, region, and size of plant or firm are ways that these constraints may play a role in this analysis.

Finally, an establishment's access to capital funds can greatly affect its costs and ability to adjust. Plants that are part of a large multi-plant firm may have greater access to internal funds and have certain types of financial credit available that are unavailable to small firm plants. In addition, interest rates paid have been shown to be strongly inversely related to the size of the borrower.[13] Thus, these costs of upsizing may be greater for single-unit, smaller establishments.

3. Data

The data used in this paper are a sample of manufacturing plants from the Longitudinal Research Database (LRD). [14] The analysis in this paper draws on the set of plants which were continuously operating over 1972-1980 and that met a certain plant-size requirement in terms of their employment (the latter is in order to ensure better quality of the hours data). The sample ends in 1980 due to data availability. The plant characteristics are: age; plant and firm size; ownership; industry; shutdown technology; region; capital, energy, and production worker intensities; and production worker wage share. These plant characteristics are collected only annually and in the analysis are held fixed over the entire sample (either at their average or 1977 value). The sample contains 9,571 manufacturing plants with about 5.7 million production workers. The sample of production worker employment tracks the total manufacturing sector relatively well (with a correlation of 0.91). In terms of the plant characteristics, the sample over represents large, older, multi-unit plants but is relatively representative in terms of most industries, location, and factor intensities. The sample is better at representing the

[13] See Brown, Hamilton, and Medoff (1990) and Davis, Haltiwanger, and Schuh (1996).

[14] The LRD is composed of data from two sources, the Census of Manufacturers (CM) and the Annual Survey of Manufacturers (ASM). The CM is conducted every five years and includes all establishments whose primary activities occur within the manufacturing sector (about 350,000 plants each census). The ASM is a rotating sample of establishments from the CM where the probability of selection for the ASM sample is related to the size of the establishment. The ASM contains roughly between 50,000 and 70,000 plants in a given year. See Davis, Haltiwanger, and Schuh (1996).

experience of manufacturing *employees* rather than the experience of manufacturing *plants*. (See Appendix A for more detail.)

A. Estimates of 2

The first step in applying this hazard methodology is calculating the state variable, employment shortages (z). As shown above in equation 4 this means estimating 2 . One issue in estimating 2 is whether it should be allowed to vary by the plant characteristics.[15] As noted above, 2 is a function of technology (" and $), wage elasticity (μ) and market structure (0). Its seems plausible that the production technology parameters especially would differ over many of the plant characteristics considered in this study as these characteristics indirectly reflect differences in production technology. The actual regression equation, which relates changes in employment to changes in hours, is derived in Appendix B.

The regression results suggest that adjustments over employment and hours do not occur in tandem; plants rely on one margin at a time. Plants initially absorb demand and cost shocks by varying hours per worker, when plants later adjust employment, the plants bring average hours per worker back to their preferred level. Thus at the plant-level, hours and employment are adjusted in opposite directions.[16]

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[15] Caballero, Engel, and Haltiwanger (1997) allow for variation by two-digit industry arguing that this "achieves a reasonable compromise between precision and flexibility (p. 120)."

[16] This tendency to adjust separately over the intensive and extensive margins has been noted by, among others, Abraham and Houseman (1992), Lilien and Hall (1986), Rones (1981), and Bry (1959). Caballero, Engel, and Haltiwanger (1995) note that this pattern is also interesting as the sign of the relationship changes at the aggregate level. "At the level of the firm, shocks are absorbed mainly along one of the two margins, while at the aggregate level the response to a given shock is shared by both margins (p. 11)."

Focusing on comparisons of the estimates within a characteristic, the largest variations in 2 are for two-digit industry. The other characteristics have 2 estimates that are remarkably similar across classes. Thus for all of the analysis that follows, the 2 used for all plant characteristics is one that varies by two-digit industry (rather than by the characteristic being analyzed). Having estimated 2, the state variable, employment shortages (z), can be created (see Appendix B).

B. Nonparametric Analysis of Employment Adjustments

The exercises in this section are intended to illuminate broad features of employment adjustments by plant characteristics without imposing structure.[17] The first exercise simply plots the relationship between the changes in employment and the employment shortages for all of the plant-quarter observations in the sample. As can be seen in Figure 1, this relationship has three distinctive features: 1) a large mass of points close to the origin (small adjustments and small shortages); 2) a mass of points scattered along the line of employment deviations at zero employment adjustments; and 3) a stark positive relationship between adjustments and shortages. In sum, the plot shows two types of behavior in reaction to employment deviations: adjustments that occur in tandem with the discrepancies and inertia in the face of discrepancies. Concerning the symmetry of adjustments, the firing side (the left side of the plot) appears to have a less steep positive relationship and more inertial episodes than the hiring side (the right side of the plot). That is, for a given absolute deviation, the firing side either adjusts by

[17] Another nonstructural exercise may be found in Foster (1998). This exercise compares the volatility of employment adjustments and shocks. The results suggest that differences in both the volatility of the underlying shocks and the adjustment costs contribute to differences in the volatility of employment adjustments.

less or is less likely to adjust.

The second exercise plots the empirical hazard function for the sample. As has been argued above, the shape of the hazard function gives information about the underlying adjustment costs and has implications for the aggregate employment dynamics. The empirical adjustment hazard function shows the average adjustment rate for a plant conditional on the size of the deviation of actual employment from desired. A plot of the empirical hazard functions can give information about the adjustment process, and thus also give an indication about the nature of the underlying employment adjustment costs, over three dimensions. First, the average vertical height of the adjustment function gives information about the average rate of adjustment and hence the level of total adjustment costs. Second, the steepness of the adjustment function relates to the relationship between the size of the discrepancy and adjustments and hence the convexity of the adjustment costs. Third, the symmetry of the curve describes differences between adjustments on the employment expansion and contraction sides and hence gives an indication of the relative importance of expansion and contraction adjustment costs. Figure 2 shows the (smoothed) empirical adjustment hazard for the entire sample of plants. The adjustment hazard is clearly increasing in the size of the employment deviation. In addition, there is an asymmetry as the adjustment rate rises more quickly over the deviations on the side of employment expansions (the right side of the plot). Together these suggest that the underlying employment adjustment costs are not convex and that adjustment costs on the contraction side exceed those on the expansion side.[18]

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[18] To summarize the results of the plots by characteristics, the adjustment hazards are increasing for all plant characteristics, however, the steepness of the adjustment hazard varies enormously. With few exceptions, the adjustment hazards are markedly asymmetric with higher adjustment rates for positive

4. Estimated Hazard Functions

The plot of the empirical hazard function described in the previous section suggests that nonlinearities and asymmetries are important at the plant level. In order to test the significance of the differences along these two dimensions, five different hazards functions embodying different assumptions about these two features are estimated. The five hazard functions are: a) constant and symmetric, b) constant and asymmetric, c) increasing and symmetric, d) increasing and asymmetric over slopes, and e) increasing and asymmetric over slopes and intercepts. The hazard functions are substituted into equation (2) to get the following *plant-level* regression equations:

(5)

$$a)\quad \Delta E_{et} = c + \lambda_0 z_{et} + \varepsilon_{et}$$

$$b)\quad \Delta E_{et} = c + \lambda_0^{-}(I^{-}(z_{et}) + \lambda_0^{+}(I^{+}(z_{et}) + \varepsilon_{et}$$

$$c)\quad \Delta E_{et} = c + \lambda_0 z_{et} + \lambda_2 z_{et}^{3} + \varepsilon_{et}$$

$$d)\quad \Delta E_{et} = c + \lambda_0 z_{et} - \lambda_1^{-}(I^{-}(z_{et}^{2}) + \lambda_1^{+}(I^{+}(z_{et}^{2}) + \varepsilon_{et}$$

$$e)\quad \Delta E_{et} = c + \lambda_0^{-}(I^{-}(z_{et}) + \lambda_0^{+}(I^{+}(z_{et}) - \lambda_1^{-}(I^{-}(z_{et}^{2}) + \lambda_1^{+}(I^{+}(z_{et}^{2}) + \varepsilon_{et}$$

Where I^- is an indicator dummy for $z<0$ and I^+ is an indicator dummy for $z\geq 0$.

The results of the estimation for the total sample are presented in Table 1. For each of the functional forms, the estimated constant is small suggesting that in the absence of an employment shortage, employment adjustments are negligible. Starting with the simplest cases, relaxing the symmetry of the constant hazard case (i.e., moving from equation 5a to 5b) yields an improvement in the adjusted R^2

employment adjustments. In many cases, the relative positions of the adjustment hazard functions by plant characteristics switches as one moves from small deviations to large deviations. See Foster (1998) for more details about the plots by characteristics.

from .409 to .422. In the asymmetric constant hazard case, the coefficient on the hiring side ($8^{+}{}_{0}$) exceeds that on the firing side ($8^{-}{}_{0}$) and this difference is significant. This result on the nature of the asymmetry is consistent with the empirical adjustment hazard. The next set of results allow for relaxing the constant hazard assumption. In both the symmetric and the asymmetric cases, this yields an improvement in the adjusted R^2. For the symmetric case, the adjusted R^2 improves from .409 to .423 (equation 5a to 5c); in the asymmetric case it goes from .422 to .462 (equation 5b to 5d). And in either case the coefficients on the increasing hazard (8_2 ; $8^{+}{}_{1}$ and $8^{-}{}_{1}$) are significant. In both cases the coefficient on the hiring side ($8^{+}{}_{1}$) exceeds that on the firing side ($8^{-}{}_{1}$) and they are significantly different from one another. Finally, there is not much improvement in moving from the increasing asymmetric functional form (equation 5d) to the combination asymmetric form (equation 5e). The second panel of Figure 2 plots the estimated adjustment hazard for the increasing asymmetric hazard case. Comparing this to the first panel in Figure 2, this estimated hazard captures the main features of the empirical hazard.

The estimates by plant characteristics are reported only for the increasing asymmetric hazard since it is the hazard that appears to best fit the data for the whole sample. All of the coefficients are allowed to vary by plant characteristics with the exception of the constant. The results, which are reported in Table 2, show that heterogeneity, nonlinearities, and asymmetry are significant at the 5% level for all eleven plant characteristics.[19] That is, over any characteristic, adjustment hazards have the same general

[19] Looking at Table 2, the three sets of F-tests can be described as:
1) Plant characteristics matter: whether the dummy classes are all zero within a characteristic for 8_0, $8^{+}{}_{1}$, and $8^{-}{}_{1}$. That is, comparing jointly all of the rows except the first one in each cell box.
2) Nonlinearities matter: whether the omitted class and dummy classes are all zero within a characteristics for $8^{+}{}_{1}$, and $8^{-}{}_{1}$. That is, comparing jointly all of the rows in each cell box.

asymmetric U-shape with the left arm lower than the right-arm, but the exact shape differs by plant characteristics. This implies that the traditional assumption of convex adjustment costs with its constant hazard is not the best representation over any plant characteristic.

Turning to the individual plant characteristic regressions, the first regression results in Table 2 show that younger plants have a higher fraction of adjusting (8_0) but have flatter slopes of the adjustment hazard function (8^+_1 and 8^-_1). Older plants have a lower fraction of adjusting over small deviations than younger plants, but over some range of large employment deviations older plants have a higher fraction of adjusting.[20] Looking at the results for plant size, smaller plants have a higher fraction of adjusting than do larger plants, but the slopes of the adjustment hazards for smaller plants are generally less steep on the side of positive adjustments (but more steep on the negative adjustment side). One interpretation is that small plants have technologies which are flexible enough to allow them to adjust to small changes or large negative changes, but that their lack of access to capital markets constrains these small plants when it comes to large positive employment adjustments. For plants grouped by firm size, one sees that the slopes of the adjustment hazard tend to be steeper for plants that are part of larger firms. The fraction of adjustment for multi-units is significantly higher than for single-units, which is consistent with the adjustment cost story in which plants in a multi-unit firm have greater access to capital funds and hence can make adjustments that entail changes in scale with more relative ease. With roughly equal

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3) Asymmetries matter: whether for each class the total effect of the nonlinear term on the positive side equals that for the negative side. That is, for each row comparing the appropriately transformed last two columns.

[20] Recall that because of the nature of the sample, all plants in the sample are aging over the sample, hence some of the age differences might be obscured by the general aging of the entire sample.

slopes, this relationship appears to hold over both small and large deviations in employment. The estimated coefficients for plants grouped by industry vary the most of any plant characteristic.[21] In many cases, there is a significant difference in the behavior of adjustments over large and small employment deviations. For example, plants in Printing have a relatively small fraction of adjusting, but this obscures the steep slope of the adjustment hazard for both positive and negative deviations. Similarly, when looking at the industry classification for shutdown technologies, plants in the continuously operating industries have a significantly lower fraction of adjusting but since they also have steeper slopes of the adjustment hazard, they have higher adjustment rates over large deviations than plants that are variable processors. Recall that plants in continuously operating industries have very high startup and shutdown costs so this is somewhat surprising. The hazards vary over regions so that in some cases the employment adjustments critically depend on the size of the deviation (e.g., Mountain has a relatively steeply sloped hazard) and in other cases, the size of the deviation does not matter as much (e.g., East South Central has a relatively flat hazard). For capital intensity, the least and most capital intense plants have the highest fractions of adjustment and relatively steep hazards on the positive side. There is no discernable pattern for plants grouped by energy intensity. The last characteristics concern the general skill level of the workforce at the plant. Production worker intensity and production worker wage shares have an increasing vertical intercept for greater production worker intensities or wage shares with the exception of the last class (note that the differences for the wage

[21] And most of these differences are significant. Out of the 190 pairs of industries, only 15 pairs of the industries fail to pass an F-test for being significantly different from one another. For the increasing hazard, pair wise F-tests have the following results concerning failures to pass: 18 pairs for the vertical intercept, 17 pairs for the positive nonlinear term, and 25 pairs for the negative nonlinear term.

share variable are mostly not significant). However, the last class of both of these production worker variables has steeper slopes on both the positive and negative adjustment sides. This suggests that for the most production worker intense and largest wage share group, the adjustment rates are higher than for the other groups over large employment deviations. Comparing just the first and last groups of these two variables, the most skilled groups (the least intensive and the smallest wage share groups) have lower vertical heights as well as flatter adjustment hazard functions. The differences between the adjustment rates of the most skilled and least skilled workers is thus greatest over the ranges of large employment deviations.

B. Distributions of Adjustment Rates

Since the hazard function is by definition the average adjustment, it may obscure a variety of plant-level behaviors. For example, it is not possible to distinguish for a given shortage whether all plants partially adjust or some plants adjust fully while others do not adjust at all. This exercise teases out some of the obscured plant-level behavior by picking three segments of the adjustment hazard function and looking at the full range of adjustments over these segments. The three segments are chosen based on the size of the employment deviation and are: large negative employment shortages (the upper left arm of the hazard function), small positive employment shortages (the section near the zero point), and large positive employment shortages (the upper right arm of the hazard function).[22] Figure 3 plots the full

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[22] The three ranges of shortages are those from Caballero, Engel, and Haltiwanger (1997) and are as follows:
1) Small positive refers to employment deviations in the range [0.2, 0.3],
2) Large negative refers to employment deviations in the range [-1.2, -0.8],
3) Large positive refers to employment deviations in the range [0.8, 1.2].

range of employment distributions over the entire sample for these three ranges. The first panel shows the distribution of adjustment rates for small employment deviations. The greatest percent of observations lies at the zero-bar with a gradual tapering off over large adjustment rates. (The negative adjustment rates represent adjustments in the "wrong" direction. These are indicative of some measurement or specification error.) The second panel shows the distribution of adjustment rates over large *negative* employment deviations. It is striking that the percent of observations that represent plants not adjusting exceeds that for small deviations. In addition, rather than tapering off the distribution of adjustment rates falls and stays flat until a small jump up at the full adjustment bar (1.0). That is, there is weak evidence of (S,s)-type of behavior over the range of large negative deviations. This (S,s)-type of behavior is more evident over the range of large *positive* deviations which is shown in the last panel. In this panel there are two distinct modes at no adjustment and full adjustment. In sum, the left arm of the hazard function appears to be dominated by inertial plants and some plants that adjust varying amounts while the right arm of the hazard function appears to be more dominated by (S,s)-type behavior. Employment smoothing is not in evidence over large employment deviations and there appears to be significant differences in adjustment behavior between the employment contraction and expansion sides. The (S,s)-type of bimodal adjustments on the positive side suggest that fixed adjustment costs are particularly important for large employment expansions (perhaps because these may entail substantial reorganizational costs as well as hiring costs). On the employment contraction side, the mode at zero adjustment indicates some inertial behavior suggesting the presence of fixed

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The two modes of adjustment are defined as follows:
1) No adjustment refers to adjustment rates in the range [-.05, .05)
2) Full adjustment refers to adjustment rates in the range [.95, 1.05).

adjustment costs, but the many instances of adjustments of different sizes suggest that many plants do not face prohibitively large fixed adjustment costs. Thus not only is the average fraction of adjusting different over the three sections of the hazard function, but the adjustment behaviors differ over these three arms.

Extending this analysis to the plant characteristics, the focus is narrowed to whether plants' employment adjustments are best described by all plants partially adjusting by the same amount or by the some plants fully adjusting while others do not adjust at all. That is, the exercise checks whether the distributions have two modes (at zero and full adjustment) or are scattered over all adjustment rates by looking at the percent of observations that are full adjustments or zero adjustments for each of the three ranges conditional on the plant characteristic in question.[23] This general pattern of inertial behavior at large negative shocks (a mode at zero), (S,s)-type behavior at large positive shocks (modes at zero and full), and varied adjustment behavior at small shocks (scattered distribution) appears in most distributions by plant characteristics. Table 3 shows a selected group of distributions of adjustment rates by plant and worker characteristics. In particular, (S,s)-type behavior (on the positive side) seems most evident for large, continuous processing, capital, energy, and skill intensive plants. This is consistent with existing literature which suggests that employment adjustments may be particularly difficult for these types of plants and hence their adjustments tend to be lumpy. However this story is not as strong when one looks at these distributions by 2-digit industry. There are some industries with bimodal behavior but there are also a significant number of industries with one mode over the range of large positive deviations.

[23] A table showing the individual results can be found in Foster (1998).

5. Aggregate Employment Dynamics

The previous sections have shown that employment dynamics at the plant-level are characterized by significant nonlinearities (including asymmetries) and by heterogeneity across plants with different characteristics. An obvious question is whether the nonlinearities and heterogeneity uncovered at the micro level significantly affect aggregate dynamics. Recall from the discussion of Caballero and Engel's characterization of aggregate employment that the aggregate dynamics reflect the interaction of the adjustment function and the cross-sectional distribution of deviations. When the adjustment hazard function is not constant, as the empirical hazards and estimations imply is the case, then the higher moments of the cross sectional distribution impact the aggregate dynamics. One would expect that the constant hazard model would perform best for those characteristics that have the flattest adjustment hazards, the narrowest distribution of deviations, and the least volatility of shocks to this distribution. That is, given an increasing adjustment hazard function, one also needs to know if the distribution of deviations is such that much of the observations are at the portions where the adjustment hazard function is steepest. This section presents two exercises intended to shed light on whether the interaction of the adjustment hazard and cross-sectional distribution is such that the nonlinearities and heterogeneity uncovered at the micro level significantly affect aggregate dynamics. The first exercise, the sectoral counterfactual analysis, compares actual sectoral employment growth rates to the growth rates implied by the nonparametric, constant, and increasing, asymmetric hazard models. The second exercise is similar but is for the aggregate level.

A. Sectoral Counterfactual Exercise

This counterfactual exercise compares the actual average sectoral employment growth rates to the predicted average sectoral employment growth rates from the nonparametric, constant, and asymmetric, increasing hazard models. In all three cases, the actual cross-sectional distribution of employment shortages is used. Furthermore, the predicted sectoral employment growth rates can be calculated allowing for differences in the adjustment hazards by plant characteristics. One measure that summarizes the differences in the actual and predicted employment growth rates is R^2 as measured below:

(6) $$R^2 \equiv 1 - \frac{\sigma^2(\Delta N^f - \Delta N)}{\sigma^2(\Delta N)}$$

Where N^f refers to forecasted sectoral employment. Unlike the R^2 for the plant-level estimations, this R^2 is not bounded below by zero and is not necessarily higher for unrestricted regressions (i.e., those allowing for either greater flexibility in the hazard function or those that allow for variation by plant characteristics) than restricted regressions.[24]

The R^2 's calculated over the different functional forms and assumptions about heterogeneity are reported in Table 4. The first row shows the R^2's for the entire sample. Since the plant-level regressions have significant nonlinearities, one would expect that the increasing, asymmetric hazard employment growth path would probably have a higher R^2 than the constant hazard employment

[24] Caballero, Engel, and Haltiwanger (1997) note that "this R^2 is not bounded below by zero since there is no restriction of a zero covariance between the predictions and residuals generated from these exercises (p. 127)." The nonparametric model appears in their decomposition as the combination of the average adjustment function and the actual cross-sectional distribution. See their table 1.

growth path and that the nonparametric case would have the highest R^2 of all three cases since it does not impose a functional form.[25] The R^2 for the total sample are ranked as expected: the employment growth path associated with the constant hazard has the worst fit and that associated with the nonparametric hazard has the best fit. This ranking holds over most of the subsequent rows which show the R^2 for each class by plant characteristic. Of the 71 characteristics, the asymmetric, increasing hazard model outperforms the constant hazard model in all but 15 cases, 9 of which are in the industry groups. There are 5 cases in which the nonparametric hazard is dominated by either (or both) of the parametric hazard models. In sum, a broad conclusion evident from the table is that at the sectoral level, the asymmetric, increasing hazard model produces an employment growth path that is more consistent with the actual employment growth path than is the employment growth path generated by the constant hazard model. Looking beyond the particular functional form chosen to represent the adjustment hazard function, in all but two cases the nonparametric employment growth path dominates the constant hazard path. That is, nonlinearities clearly matter at the sectoral level.

Switching the focus to plant heterogeneity, comparing the R^2 across the rows of Table 4, one sees a tremendous amount of variation. Repeating a pattern that has been consistent across the different empirical exercises, the largest variation in the results occurs for plants grouped by industry. Not surprisingly given the often offsetting interaction of the adjustment hazard function shape and distribution of deviations there are not many clear cut patterns in the R^2 by plant characteristic. For example, recall that young plants have relatively flat adjustment hazards suggesting that of the age groups this would

[25] Obviously the plant-level regression R^2's are higher for the asymmetric, increasing hazard case than for the constant hazard case.

have the highest R^2 for the constant hazard model. On the other hand, there is evidence in the literature that young plants face very volatile shocks, which suggests that much of the observations might occur over the relatively more nonlinear parts of the hazard and hence the R^2 for the constant hazard would be relatively low.[26] As it is, the constant hazard model performs most poorly for the oldest plants (steeper adjustment hazard functions, but relatively less volatile shocks). A similar story of the offsetting effects of the shape of the adjustment function and the cross-sectional distribution holds for plant and firm size and hence its not surprising that no clear pattern over size classes emerges for these characteristics either. For both plant and firm size, the smallest classes have the flattest hazards and yet are subject to the most volatile shocks. Similarly, single unit plants face more volatile shocks and have flatter hazards than plants that are part of multi-unit firms.

As noted above, the greatest variation in R^2 by plant characteristic occurs by industry. Two of the industries where one would expect to see interesting differences in the counterfactuals are in Tobacco and Paper as these represent opposite extremes of the hazard shapes. Tobacco has a very steep adjustment hazard while Paper has a flatter adjustment hazard and hence one would expect *ceteris paribus* nonlinearities to be more important for Tobacco. Looking at Table 4, these expectations are borne out: the improvement in the R^2 in going from the constant hazard model to the nonparametric hazard is .109 for Tobacco and only .018 for Paper. Still it is important to keep in mind that the steepness of the adjustment hazard function and the shock volatility can have offsetting effects making it difficult to predict how relatively important the nonlinearities will be. Turning to industries by shutdown

[26] See Dunne, Roberts, and Samuelson (1989); Davis, Haltiwanger, and Schuh (1996); and Foster (1998).

technology, continuous processors which has a hazard that is relatively flat up to large positive shortages where it becomes relatively steep, has the highest R^2 for the employment path associated with the constant hazard. For regions, an example of the differences in nonlinearities significance can be seen by comparing Mountain with its relatively steep hazard to West South Central with its relatively flat hazard on the positive side. In moving from a constant hazard to an increasing hazard, the R^2 improves for Mountain, but actually falls for West South Central. The nonlinearities have most of their effect on the higher classes of capital and energy intensity. It is also the case that the nonlinearities have their greatest effect on the least skilled workers (the most intensive and largest wage share group). Recall that these skill groups tended to have steeper hazards.

B. Aggregate Counterfactual Exercise

One can conduct a similar counterfactual exercise at the aggregate level. The R^2 calculated over the different functional forms and assumptions about heterogeneity are reported in Table 5. At the most general level of comparison, allowing for nonlinearities (i.e., comparing column 2 to column 1) has more impact on the goodness of fit than does allowing for heterogeneity by plant characteristic (i.e., comparing row 1 to any subsequent row). This is also generally true even when the nonlinearity is assumed to be represented by the asymmetric, increasing hazard model.[27] Comparing across hazard functional forms (i.e., across columns), the R^2 increase from the constant hazard to the asymmetric hazard to the nonparametric hazard. The relative importance of the nonlinearities differs by plant

[27] The one exception is industry: under a constant hazard model, allowing for hazards to vary by industry has more of an effect on R^2 than does moving from a constant model that varies by industry to an increasing, asymmetric model that varies by industry.

characteristics (but not as strikingly as at the sectoral level); nonlinearities matter most for production worker intensity and least for industry and region.

Although not as important as nonlinearities, in general, heterogeneity also matters at the aggregate level. Comparing adjustment hazards for the total sample to those by plant characteristics (i.e., comparing the first row to subsequent rows) shows that, with few exceptions, the R^2 improve when allowing for differences by plant characteristics. Regardless of the specification, the R^2 improve the most when allowing for differences across industry and across region. On the other hand, ownership and shut-down technology either show very little improvement or actually have lower R^2 than for the total case. In some cases, allowing for the hazards to vary by plant characteristics matters more under different adjustment hazard functional forms. For example, as compared to the total sample production worker intensity adds very little explanatory power in the constant model (.633 vs. .635) but is more important in the increasing, asymmetric model (.683 vs. .692). Plant and firm size have the opposite pattern: allowing the hazard to vary over either size measure increases the R^2 of the constant hazard function (.633 vs. .643 and .643), but has no virtually no effect on the asymmetric, increasing hazard function (.683 vs. .683 and .684). Although the micro-level empirical and estimated hazards strongly reject the constant hazard model for all plant characteristics, it still may be the case that at the aggregate level, the dynamics associated with the constant hazard case may be more suitable for some plant characteristics than others.

6. Conclusions

This paper has explored employment adjustments at the establishment and aggregate levels by applying the theoretical framework of state-dependent hazards to an empirical analysis of highly disaggregated data. The following conclusions emerge from the various exercises undertaken in this paper.

1. At the micro level, adjustments at the intensive (hours) and extensive (employment) margins are undertaken separately. This holds for plants grouped by any of the plant characteristics considered here. The largest variation in this relationship occurs over plants grouped by their two-digit industry classification.

Although this paper focuses exclusively on adjustments over the employment margin, in order to create the state variable the relationship between hours growth and employment growth is estimated. Estimates over all of the plant characteristics show a negative relationship between hours growth and employment growth at the micro level. This suggests that plants initially absorb demand and cost shocks by varying hours per worker, and then when they later adjust employment, bring average hours per worker back to their preferred level. This runs counter to the relationship at the aggregate level where the correlation between hours per worker and employment adjustments is positive. This result serves as yet another example of how aggregation obscures the underlying micro interactions.

2. Adjustment hazards for plants are increasing and asymmetric. This finding holds for the total sample and for plants grouped by any of the plant characteristics in consideration. Nevertheless, within this general functional form, there are significant differences in the adjustment hazards by plant characteristics.

The increasing nature of the adjustment hazard means that plants with large (absolute) deviations adjust disproportionately more than plants with small (absolute) deviations. The asymmetry is such that plants with positive employment deviations adjust disproportionately more than plants with negative employment deviations of the same magnitude. Using a parametric approach and applying significance tests to estimates of the adjustment hazard functions reveals that the nonlinearities are significant for each of the eleven plant characteristics. Applying significance tests to the estimates of the asymmetries shows that the apparent difference between the contraction and expansion side estimates is significant for each of the classes of the eleven plant characteristics. However, within this general functional form, there are significant differences in the height and steepness of the U-shaped adjustment function even across classes within a plant characteristic. The most striking differences within a characteristic occur across industry classes.

3. The plant-level employment adjustments underlying the adjustment hazard show different behavior depending on whether the employment shortage is large and negative, close to zero, or large and positive. This general pattern is repeated for most plant characteristics.

The empirical adjustment hazard by definition shows average adjustment rates as a function of employment shortages and hence can obscure very different plant-level adjustment behavior. For example, for a given shortage, it could be that all plants adjust by the average amount or some plants adjust fully while others do not adjust at all. One exercise picks three segments of the adjustment rate function hazard and looks at the distributions of adjustments over these segments in more depth. The pattern that emerges is that there are three different general behaviors depending on the size and sign of the employment shortage. In short, there is a substantial amount of inertial behavior for large negative employment shortages, there is varied behavior over shortages close to zero, and (S,s)-type of bimodal adjustments to shocks (either no adjustment or full adjustment) in response to large positive employment deviations. Although the general finding holds over most plant characteristics, there are notable exceptions. For instance, for industry classes, much of the adjustments over the large positive range of deviations have only one mode (either zero or full adjustments but not both).

4. At the sectoral level, the employment growth path associated with the asymmetric, increasing hazard more closely matches the actual employment growth path than that associated with the constant hazard for almost all of the values of any of the plant characteristics. Nevertheless, the importance of nonlinearities differs over many of the plant characteristics.

The aggregate implications at the sectoral level of the micro nonlinearities are evaluated via a sectoral counterfactual exercise. This exercise compares a measure of the goodness of fit relative to the actual employment growth path for the path predicted by each of the three alternate hazard functions (nonparametric, constant, and asymmetric, increasing). The sectoral employment growth path results from the interaction of the hazard function with the distribution of employment deviations. For example, if the micro hazard is highly nonlinear and/or the sector is subject to a high variability of sectoral or idiosyncratic shocks, then the micro nonlinearities will, by construction, be more important at the aggregate level. In some cases, the hazard and volatility of employment deviations have offsetting effects making predicting the relative importance of nonlinearities difficult. At the sectoral level, the employment path associated with the nonparametric hazard (and to a lesser extent that of the asymmetric, increasing hazard) dominates that of the constant hazard. The conclusion is that nonlinearities clearly matter at the sectoral level. The importance of these nonlinearities varies over the plant characteristics, with the most variation across industries.

5. At the aggregate level, accounting for nonlinearities (including asymmetries) is more important than accounting for plant heterogeneity.

A similar counterfactual exercise compares the goodness of fit relative to the actual employment growth path at the total manufacturing aggregate level for the path predicted by each of the three adjustment hazard functions. For this exercise, the nonlinearities and allowing the hazards to vary at the micro level by observable plant characteristics are both evaluated in terms of their contribution to aggregate total manufacturing employment dynamics. For the total sample and for any plant characteristic, the employment path predicted by the nonparametric hazard has a better fit relative to the actual employment path than the constant hazard path. The relative importance of the nonlinearities differs by plant characteristics (but not as strikingly as at the sectoral level), nonlinearities matter most for production worker intensity and least for industry and region. Allowing for plant heterogeneity also improves the goodness of fit but it is not as important as allowing for nonlinearities at the aggregate level. The largest improvement in the measure of goodness of fit for allowing for heterogeneity occurs for industry (over any of the hazards). In sum, the nonlinearities (including asymmetries) and plant heterogeneity uncovered at the establishment level have a significant impact on aggregate employment growth.

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Figure 1: Employment Changes and Employment Shortages

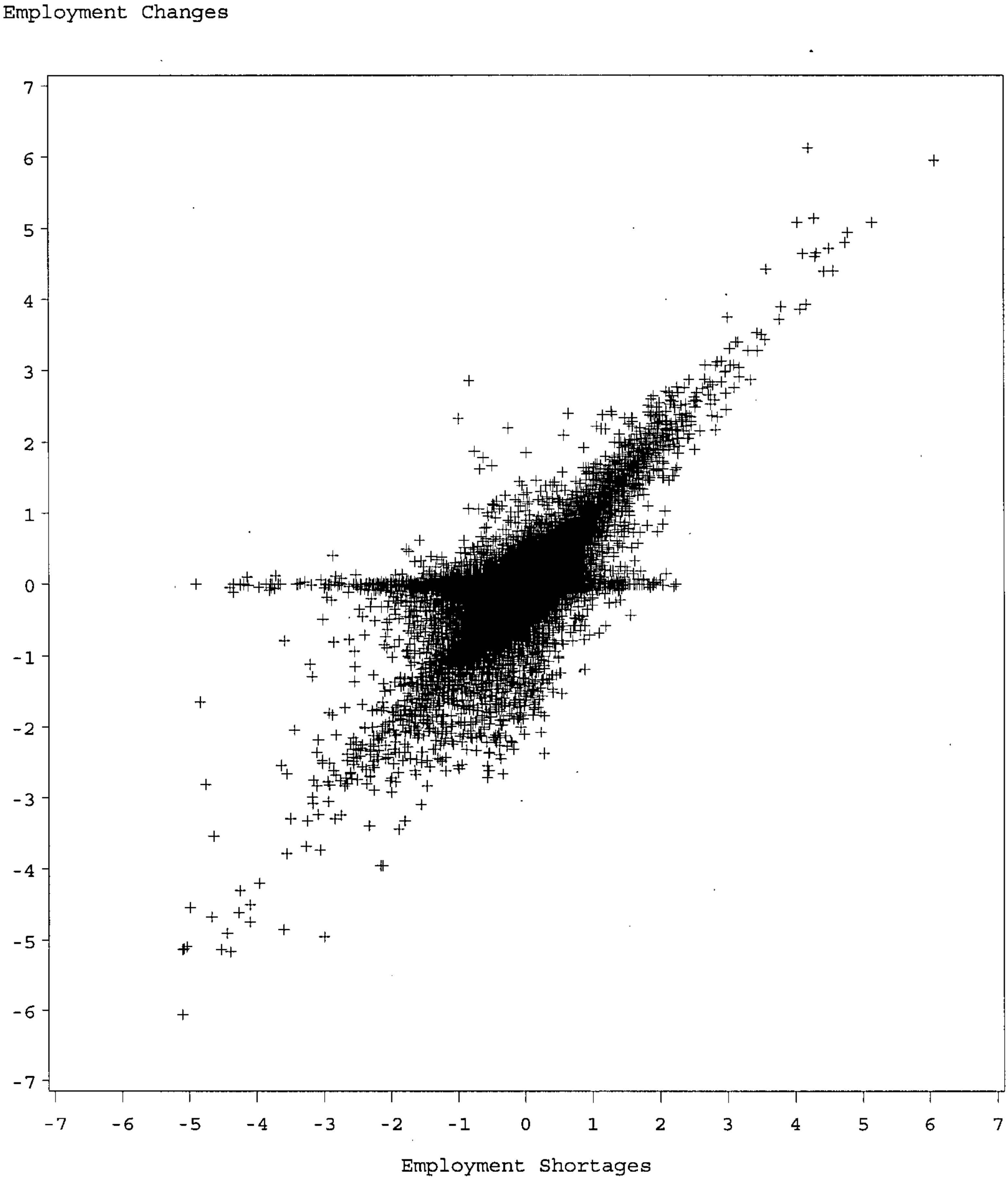
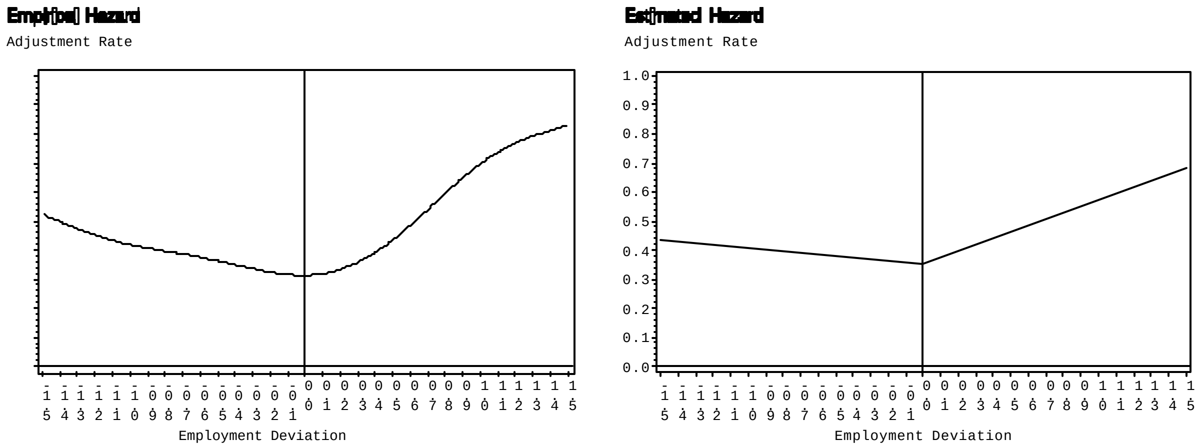


Figure 2: Adjustment Hazards



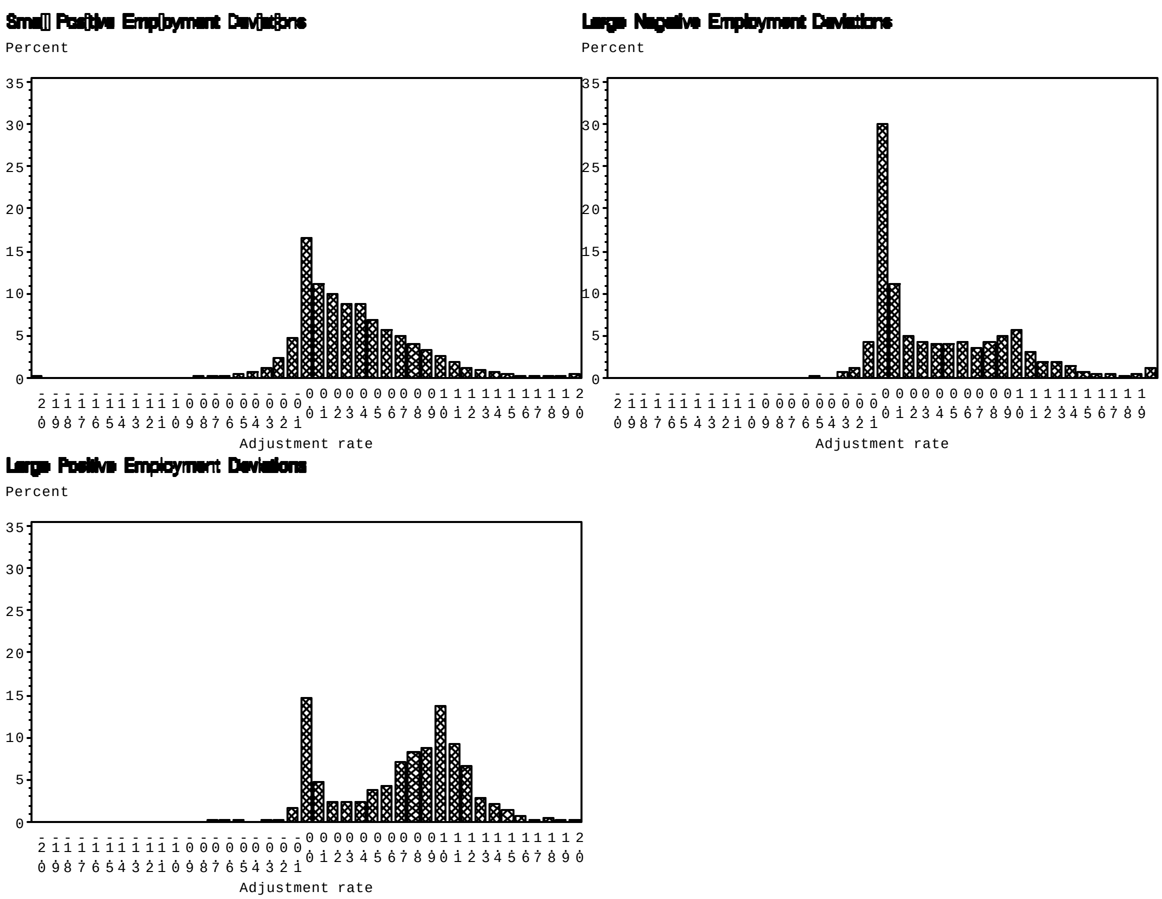


Figure 3: Distributions of Adjustment Rates

Table 1: Hazard Estimations over Various Functional Forms for Total Sample (OLS[1], using plant level data)					
	Functional Form of Hazard				
Parameter	Constant, Symmetric	Constant, Asymmetric	Increasing, Symmetric	Increasing, Asymmetric	Combination, Asymmetric
c	.002 * (.000)	-.015 * (.000)	.002 * (.000)	-.002 * (.000)	-.005 * (.000)
8_0	.478 * (.001)		.440 * (.001)	.351 * (.001)	
8^+_0		.600 * (.002)			.371 * (.002)
8^-_0		.386 * (.001)			.335 * (.002)
8^+_1				.220 * (.001)	.212 * (.002)
8^-_1				-.055 * (.001)	-.061 * (.001)
8_2			.015 * (.000)		
Adjusted R^2	.409	.422	.423	.462	.462

* Individual coefficient estimate significant at the 5% level.
For each specification, where relevant, coefficients on the asymmetries are significantly different from one another at the 5% level.

1/ Regressions use desired employment based on $2_{2\text{-digit}}$. There are two potential difficulties of using OLS to estimate these adjustment functions: specification error in choosing the adjustment hazard functional form and measurement error for the employment deviation variable. These imply that an IV estimation may be warranted (see Griliches and Hausman (1986)). An IV estimation yields coefficients that are consistent with asymmetry and an increasing hazard. Furthermore, Caballero, Engel, and Haltiwanger (1995) provide evidence that classical measurement error will tend to obscure evidence of an *increasing* hazard.

Table 2: Increasing, Asymmetric Hazard Estimation by Plant Characteristics

For each panel, the first row reports the coefficient on the omitted characteristic. Subsequent rows report the coefficients on the dummy variable associated with that characteristic.

Plant Characteristic	Height (8_0)	Positive side (8^+_1)	Negative side (8^-_1)
Age			
Youngest (1)	.42 (.009) *	.18 (.007) *	.04 (.010) *
Medium (2)	-.05 (.009) *	.01 (.007)	-.09 (.010) *
Oldest (3)	-.09 (.009) *	.07 (.007) *	-.10 (.010) *
Plant Size			
250-499 (1)	.36 (.002) *	.21 (.001) *	-.08 (.001) *
500-999 (2)	-.01 (.003) *	.03 (.003) *	.04 (.002) *
1000-2499 (3)	-.04 (.005) *	.05 (.006) *	.09 (.003) *
2500-4999 (4)	.01 (.008)	-.03 (.007) *	.10 (.005) *
5000 or more (5)	-.07 (.010) *	.09 (.008) *	.03 (.003) *
Firm Size			
250-499 (1)	.34 (.003) *	.22 (.003) *	-.10 (.003) *
500-999 (2)	.01 (.005) *	.00 (.005)	-.02 (.004) *
1000-2499 (3)	.02 (.005) *	.01 (.004) *	.01 (.004) *
2500-4999 (4)	.02 (.005) *	.05 (.005) *	.06 (.004) *
5000-9999 (5)	-.03 (.005) *	.02 (.005) *	.08 (.004) *
10000-24999 (6)	.00 (.004)	-.04 (.004) *	.06 (.004) *
25000-49999 (7)	-.06 (.006) *	.05 (.006) *	.06 (.004) *
50000 or more (8)	.06 (.007) *	.07 (.009) *	.17 (.009) *
Ownership			
Multi-Unit	.35 (.001) *	.22 (.001) *	-.05 (.001) *
Single Unit	-.02 (.006) *	.00 (.007)	-.01 (.006)

Table 2: Increasing, Asymmetric Hazard Estimation by Plant Characteristics

For each panel, the first row reports the coefficient on the omitted characteristic. Subsequent rows report the coefficients on the dummy variable associated with that characteristic.

Plant Characteristic	Height (8_0)	Positive side (8^+_1)	Negative side (8^-_1)
Industry			
Food (20)	.35 (.004) *	.29 (.003) *	-.12 (.003) *
Tobacco (21)	.57 (.018) *	-.30 (.013) *	.26 (.011) *
Textile Mill (22)	-.03 (.008) *	.03 (.012) *	-.00 (.009)
Apparel (23)	.09 (.008) *	-.14 (.007) *	.12 (.011) *
Lumber (24)	-.10 (.009) *	-.07 (.007) *	.02 (.007) *
Furniture (25)	-.14 (.009) *	.02 (.008) *	-.09 (.007) *
Paper (26)	-.15 (.008) *	-.07 (.007) *	.09 (.004) *
Printing (27)	-.09 (.009) *	.07 (.014) *	.05 (.009) *
Chemicals (28)	-.09 (.007) *	-.03 (.007) *	.06 (.004) *
Petroleum (29)	-.14 (.017) *	-.00 (.013)	.02 (.008) *
Rubber & Plastics (30)	.09 (.008) *	-.12 (.007) *	.08 (.005) *
Leather (31)	.04 (.015) *	.13 (.029) *	-.03 (.025)
Stone, Clay, Glass (32)	-.05 (.009) *	.01 (.009)	.05 (.005) *
Primary Metals (33)	-.05 (.007) *	-.06 (.005) *	.03 (.004) *
Fabricated Metals (34)	-.05 (.006) *	-.11 (.004) *	.02 (.004) *
Machinery ex. Elect. (35)	-.07 (.005) *	-.10 (.004) *	.07 (.004) *
Electrical Machinery (36)	.07 (.006) *	-.03 (.008) *	.08 (.006) *
Transportation (37)	.07 (.006) *	-.04 (.006) *	.08 (.003) *
Instruments (38)	-.07 (.009) *	-.08 (.008) *	.08 (.009) *
Miscellaneous (39)	.14 (.010) *	-.14 (.009) *	.11 (.011) *

Table 2 (con't): Increasing, Asymmetric Hazard Estimation by Plant Characteristics

For each panel, the first row reports the coefficient on the omitted characteristic. Subsequent rows report the coefficients on the dummy variable associated with that characteristic.

Plant Characteristic	Height (8_0)	Positive side (8^+_1)	Negative side (8^-_1)
Shutdown Technology			
Variable	.37 (.002) *	.21 (.002) *	-.06 (.001) *
Continuous	-.10 (.005) *	.05 (.004) *	-.03 (.003) *
Other	-.03 (.003) *	.03 (.003) *	.05 (.002) *
Not Classified	.01 (.006)	-.03 (.004) *	-.01 (.005)
Region			
New England (1)	.30 (.006) *	.27 (.009) *	-.00 (.007)
Middle Atlantic (2)	-.02 (.007) *	-.02 (.010)	-.09 (.008) *
East North Central (3)	.04 (.007) *	-.06 (.010) *	-.03 (.008) *
West North Central (4)	.07 (.008) *	-.04 (.011) *	-.06 (.009) *
South Atlantic (5)	.06 (.007) *	-.08 (.010) *	-.08 (.008) *
East South Central (6)	.06 (.008) *	-.09 (.010) *	-.05 (.008) *
West South Central (7)	-.01 (.008)	-.07 (.010) *	-.09 (.008) *
Mountain (8)	.05 (.011) *	.03 (.013) *	-.15 (.010) *
Pacific (9)	.11 (.007) *	-.01 (.010)	-.05 (.008) *

Table 2 (con't): Increasing, Asymmetric Hazard Estimation by Plant Characteristics

For each panel, the first row reports the coefficient on the omitted characteristic. Subsequent rows report the coefficients on the dummy variable associated with that characteristic.

Plant Characteristic	Height (8_0)	Positive side (8^{+}_{1})	Negative side (8^{-}_{1})
Capital Intensity			
Class 1 (lowest)	.37 (.003) *	.25 (.004) *	-.04 (.003) *
Class 2	-.05 (.004) *	-.08 (.005) *	-.05 (.004) *
Class 3	-.03 (.004) *	-.02 (.005) *	-.01 (.004) *
Class 4	-.02 (.004) *	.00 (.005)	-.03 (.004) *
Class 5 (highest)	-.01 (.004) *	.00 (.005)	-.00 (.004)
Energy Intensity			
Class 1 (lowest)	.38 (.003) *	.19 (.002) *	-.05 (.002) *
Class 2	-.08 (.004) *	.07 (.004) *	-.03 (.003) *
Class 3	-.02 (.004) *	.02 (.003) *	.04 (.003) *
Class 4	.00 (.004)	.07 (.004) *	.02 (.003) *
Class 5 (highest)	-.05 (.004) *	.04 (.003) *	-.03 (.002) *
Prod. Worker Intensity			
Class 1 (lowest)	.27 (.003) *	.19 (.002) *	-.07 (.002) *
Class 2	.04 (.004) *	.06 (.004) *	.01 (.003) *
Class 3	.09 (.004) *	.03 (.004) *	.02 (.003) *
Class 4	.13 (.004) *	.02 (.004) *	.05 (.003) *
Class 5 (highest)	.10 (.004) *	.05 (.004) *	-.04 (.003) *
Prod. Worker Wage Share			
Class 1 (lowest)	.28 (.003) *	.19 (.002) *	-.10 (.002) *
Class 2	.04 (.004) *	.03 (.004) *	.06 (.003) *
Class 3	.06 (.004) *	.04 (.004) *	.05 (.003) *
Class 4	.14 (.004) *	.03 (.004) *	.10 (.003) *
Class 5 (highest)	.08 (.004) *	.04 (.003) *	-.04 (.003) *

* Individual coefficient estimate significant at the 5% level.

Table 3: Selected Distributions of Adjustment Rates over Three Ranges of Shortages
Percent of Observations at the No Adjustment and Full Adjustment Nodes

Characteristic	Large Negative		Small Positive		Large Positive	
	No	Full	No	Full	No	Full
Total Manufacturing	30.1 *	5.7	16.6 *	2.6	14.7 *	13.7 *
Age Oldest (3)	31.8 *	5.8	17.4 *	2.3	14.1 *	13.1 *
Plant Size 5000 or more (5)	44.4 *	3.7	21.9 *	2.6	11.1 *	44.4 *

Firm Size 50000 or more (8)	30.8 *	4.7	17.2 *	3.1	9.5	19.0 *
Ownership Multi-unit (2)	30.3 *	5.6	16.6 *	2.6	14.6 *	13.8 *
Industry Textile Mill (22)	19.1 *	8.5	12.4	3.6	20.8 *	29.2 *
Shutdown Technology Continuous processors (2)	47.0 *	3.0	20.2 *	2.2	15.0 *	25.0 *
Region New England (1)	37.2 *	3.5	16.5 *	2.3	17.5 *	17.5 *
Capital Intensity Class 5 (highest)	35.0 *	5.4	18.6 *	1.8	11.4 *	19.2 *
Energy Intensity Class 5 (highest)	35.0 *	6.4	18.1 *	2.2	12.7 *	21.5 *
Prod. Worker Intensity Class 1 (lowest)	36.3 *	4.4	18.9 *	2.7	20.3 *	13.0 *
Prod. Worker Wage Share Class 1 (lowest)	36.5 *	3.4	18.2 *	2.9	18.6 *	11.2

* Denotes that the percent of observations at this node is one of the two highest in the distribution.

The three ranges of shortages are as follows:
1) Large negative refers to employment deviations in the range [-1.2, -0.8]
2) Small positive refers to employment deviations in the range [0.2, 0.3]
3) Large positive refers to employment deviations in the range [0.8, 1.2].

The two nodes of adjustment are as follows:
1) No refers to adjustment rates in the range [-.05,.05)
2) Full refers to adjustment rates in the range [.95, 1.05).

Table 4: Sectoral Counterfactual Exercise Comparing Predicted Values of Employment Growth. (R^2 of the predictions.)

Plant Characteristic	Nonparametric Hazard	Constant Hazard	Increasing, Asymmetric Hazard
Total Manufacturing	.702	.633	.683
Age			
Youngest (1)	.862	.765	.787
Medium (2)	.774	.767	.765
Oldest (3)	.660	.521	.624
Plant Size			
250-499 (1)	.706	.623	.688
500-999 (2)	.708	.638	.671
1000-2499 (3)	.618	.575	.556
2500-4999 (4)	.761	.639	.694
5000 or more (5)	.722	.501	.483
Firm Size			
250-499 (1)	.691	.654	.705
500-999 (2)	.729	.579	.648
1000-2499 (3)	.741	.528	.688
2500-4999 (4)	.670	.580	.622
5000-9999 (5)	.628	.577	.583
10000-24999 (6)	.727	.688	.704
25000-49999 (7)	.655	.561	.585
50000 or more (8)	.780	.701	.724
Ownership			
Single unit (1)	.663	.561	.624
Multi-unit (2)	.704	.635	.685
Industry			
Food (20)	.840	.662	.776
Tobacco (21)	.955	.846	.869
Textile Mill (22)	.693	.484	.650
Apparel (23)	.731	.686	.695
Lumber (24)	.763	.685	.679
Furniture (25)	.703	.613	.709
Paper (26)	.541	.523	.474
Printing (27)	.645	.155	.393
Chemicals (28)	.553	.535	.533
Petroleum (29)	.709	-.333	.318
Rubber & Plastics (30)	.802	.719	.707
Leather (31)	.556	.459	.504
Stone, Clay, Glass (32)	.696	.687	.621
Primary Metals (33)	.755	.694	.744
Fabricated Metals (34)	.594	.527	.555
Mach. ex. Elect (35)	.653	.637	.635
Electrical Mach. (36)	.650	.600	.597
Transportation (37)	.779	.732	.723
Instruments (38)	.446	.463	.433
Miscellaneous (39)	.630	.533	.534

Table 4 (con't): Sectoral Counterfactual Exercise Comparing Predicted Values of Employment Growth. (R^2 of the predictions.)

Plant Characteristic	Nonparametric Hazard	Constant Hazard	Increasing, Asymmetric Hazard
Shutdown Technology			
Variable (1)	.685	.557	.641
Continuous (2)	.670	.718	.679
Other (3)	.709	.679	.691
Not classified (4)	.750	.708	.720
Region			
New England (1)	.314	.154	.223
Middle Atlantic (2)	.438	.334	.428
East N. Central (3)	.706	.688	.683
West N. Central (4)	.745	.706	.711
South Atlantic (5)	.757	.516	.701
East S. Central (6)	.721	.672	.676
West S. Central (7)	.772	.763	.727
Mountain (8)	.900	.777	.865
Pacific (9)	.825	.661	.750
Capital Intensity			
Class 1 (lowest)	.732	.732	.741
Class 2	.646	.643	.658
Class 3	.700	.622	.658
Class 4	.721	.514	.654
Class 5 (highest)	.749	.641	.722
Energy Intensity			
Class 1 (lowest)	.740	.714	.727
Class 2	.688	.659	.674
Class 3	.641	.571	.596
Class 4	.719	.578	.670
Class 5 (highest)	.764	.583	.727
Prod. Worker Intensity			
Class 1 (lowest)	.534	.469	.503
Class 2	.596	.523	.549
Class 3	.709	.663	.696
Class 4	.759	.711	.734
Class 5 (highest)	.757	.454	.687
Prod. Worker Wage Share			
Class 1 (lowest)	.538	.499	.530
Class 2	.599	.550	.575
Class 3	.708	.669	.681
Class 4	.775	.730	.752
Class 5 (highest)	.758	.413	.682

Table 5: Aggregate Counterfactual Exercise Comparing Predicted Values of Employment Growth. (R^2 of the predictions.)			
Plant Characteristic	Nonparametric Hazard	Constant Hazard	Increasing, Asymmetric Hazard
Total Manufacturing	.702	.633	.683
Age	.711	.635	.687
Plant Size	.714	.643	.683
Firm Size	.718	.643	.684
Ownership	.704	.632	.683
Industry	.737	.677	.701
Shutdown Technology	.704	.628	.677
Region	.721	.661	.697
Capital Intensity	.707	.638	.687
Energy Intensity	.716	.634	.686
Production Worker Intensity	.720	.635	.692
Production Worker Wage	.710	.638	.691

APPENDIX A: Data

To get a more complete picture of the representativeness of the sample, I compared the sample to the total population over the plant characteristics in this study using the 1977 Census. In 1977, there were 350,648 manufacturing plants with 13.7 million production workers. In general, the sample performs reasonably well over the plant characteristics except for the age and size variables. Given that the sample is of continuously operating plants, it is certain that the sample is more skewed to older plants than is the population (it is not possible to measure age for all plants in 1977). The sample plant-size distribution is much more concentrated in the middle to large plants than is the total distribution. This is mitigated if one looks at the distribution weighted by total employment since in manufacturing most plants are small but most employees work at large plants. Hence the sample is more representative of the average employee than of the average plant. This pattern holds for each plant characteristic. Plants that are part of a large firms and/or a multi-unit firm are over-represented in the sample. With a few exceptions, the sample matches total manufacturing relatively well by two-digit industries. One would expect that industries with small plants or where births and deaths are concentrated to be under represented. This is evident in the Mattey-Strongin classification of industries by shutdown technology where continuous processors, which tend to be larger plants, are over represented in the sample. In terms of regions, the sample tracks the total generally well. Finally, the mean factor intensities and skill variables are relatively similar over the two groups of plants.

Derived Variable Definitions

Each of the 4 intensity variables are divided into 5 classes based on the distribution of each plant's average intensity over the sample in these classes.

Age: Plants are assigned to age classes based on their age in 1972: young (0-2 years), medium (3-15 years), and old (16 years or older). Plant age is determined by using the birth year of the plant which is measured as the minimum of the year in which the plant first appeared in the LRD and the birth year reported in the 1975 and 1981 ASMs.

Capital Intensity: The capital-labor ratio is the ratio of real equipment and structures capital stocks to total long-run average employment. Real capital stocks are generated by the perpetual inventory method using a measure of real investments (see Adams and Jaffe (1994)).

Energy Intensity: Energy intensity is the ratio of the cost of fuels and electricity to total value of shipments of the plant.

Production worker intensity: The production-worker intensity is the share of production worker employment in total employment at the plant. The production-worker wage share is measured as the ratio of production worker compensation to total worker compensation.

Shutdown Technology: Plants are divided into three groups (continuous processing, assembly-type, and other) using Mattey and Strongin's (1994) classification of 1977 four-digit industries (1972 SIC) and a fourth category of not classified industries.

Size: Plant size is the number of total employees. Firm size is the geometric average of the number of total employees in Census years 1972 and 1977. Plant and firm sizes are divided into classes.

APPENDIX B: Measuring the State Variable

Recall that the first task in implementing a state-hazard approach is to measure the state variable. In this case, the state variable is the deviation in actual employment from the frictionless employment level. This paper uses the state variable as defined in Caballero, Engel, and Haltiwanger (1997). As in the Caballero and Engel (1993) model, agents in the Caballero, Engel, and Haltiwanger (henceforth CEH) framework would keep hours constant in a frictionless world, but use hours to adjust to shocks when employment adjustment costs exceed those of hours. Thus hours per worker at a plant contains information concerning the plant's employment shortages. Following the latest round of adjustments, the employment shortage (z^1) is related to the excess of hours relative to the frictionless constant ($\bar{h}$ at a plant):

(7) $$z_{et}^{1} = \theta_e (h_{et} - \bar{h}_e)$$

Then the state variable which measures the deviation in actual from desired prior to the latest employment adjustments is just:

(8) $$z_{et} = \theta_e (h_{et} - \bar{h}_e) + \Delta n_{et}$$

As a first step in being able to estimate the parameter θ in the above equation, the equation can be rewritten by substituting in the definition of z and taking the first differences:

(9) $$\Delta n_{et} = \Delta n_{et}^{*} - \theta_e \Delta h_{et}$$

Or equivalently the key equation for measuring the employment gap is,

(10) $$\Delta z_{et} = \theta \Delta h_{et}$$

Once one has θ and the initial conditions one can measure the employment deviation. With the assumption that

(11) $$\sum_{t=0}^{T} z_{et} = 0$$

one can generate the initial employment deviation (z_{e0}) given equation (10). Then using equation (10) and the initial employment deviation one can generate the entire time path of deviations.

To estimate θ they exploit equation (9) in the following manner. Defining ε as an error term encompassing both the shock Δn^* and measurement error terms, equation (9) then can be rewritten as the regression equation:

(12) $$\Delta n_{et} = constant_e - \theta_e \Delta h_{et} + \varepsilon_{et}$$

In practice CEH note, this regression is likely to yield downward-biased results for two reasons. The first problem is that changes in hours and the error term are positively correlated (through the part of the error term that is due to frictionless shocks). A partial solution used by CEH is to use only large changes in employment and hours in the estimations (as in these episodes the changes should be of one order of magnitude larger than the error). The second problem is that the measurement error in hours and changes in hours are positively correlated. To reduce this problem, they run a reverse regression using employment, which yields an upward biased estimate. When both the independent and dependent variables are subject to measurement error, the interval between the OLS regression and reverse regression contains the value of the coefficient. It is assumed that the measurement errors for the two variables are uncorrelated and have equal variance which are themselves equal to the variance of the signals. Under the assumption that the ratio of measurement errors' variances is unity, the appropriate estimator is the orthogonal regression estimator which minimizes the sum of squared perpendicular distances of the observed dependent variable from the regression line.[28] Hence they pick a value from this interval by taking the convex combination of the two estimations where the weights are chosen to minimize the mean-squared error of the estimator.[29]

[28] See Kmenta (1986) p. 355 and Kennedy (1992) p. 146.

[29] In practice, the regression algorithm includes a correction for small samples.