Aggregate Employment Dynamics:
Building from Microeconomic Evidence

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This paper studies quarterly employment flows of approximately 10,000 U.S. manufacturing establishments. We use establishments' hours-week to construct measures of the deviation between desired and actual employment and use these as the establishments' main state variables. Our main findings are: (i) microeconomic adjustment functions are nonlinear, with plants adjusting disproportionately to large shortages; (ii) adjustments are often either large or nil, suggesting the presence of nonconvexities in the adjustment cost technologies; (iii) the bulk of average employment fluctuations is accounted for by aggregate, rather than reallocation, shocks; and (iv) microeconomic nonlinearities amplify the impact of large aggregate shocks. (JEL E24, J41, J6)

Since adjusting employment is costly, microeconomic employment levels often deviate from what would be optimal in the absence of frictions. In the presence of adjustment costs,

establishments' employment choices depend not only on exogenous current and expected future conditions, but also on past employment decisions. At each point in time, an establishment inherits a deviation between "desired" and actual employment levels (employment shortage), reflecting its incomplete adjustment during previous periods. New aggregate and idiosyncratic shocks modify this employment shortage, and what is left of it after the plant's adjustment during the current period is bequeathed to the next period. Following this chain of events methodically for a large number of establishments can shed substantial light on many important aspects of microeconomic and macroeconomic employment adjustment.[1]

[1] There are several strands of literature related to this paper. On many aspects of the methodology and qualitative findings, the paper is closely linked to the literature on aggregate dynamics in the presence of fixed costs on microeconomic adjustment [(S, s) models]. See, e.g., Alan S. Blinder (1981), Andrew S. Caplin (1985), Caplin and Daniel F. Spulber (1987), Giuseppe Bertola and Caballero (1990), Joseph J. Beaulieu (1991), Caballero and Engel (1991, 1992, 1993), Caplin and John Leahy (1991), Avner Bar-Ilan and Blinder (1992), Caballero (1993), Daniel S. Hamermesh (1993), and Janice C. Eberly (1994). There is a closely related literature that (like this paper) exploits plant-level data to investigate the importance of lumpy changes in plant-level employment (see, e.g., Hamermesh, 1989; Steven J. Davis and Haltiwanger, 1992; Timothy F. Bresnahan and Valerie A.

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This paper characterizes and organizes U.S. manufacturing plant-level employment data accordingly.[2]

We start by relating the changes in a plant's employment shortage to the fluctuations in the plant's hours per worker. Conditional on these measures of shortages and on actual employment adjustments, we recover aggregate and idiosyncratic shocks from simple "accounting" relationships. We then study the relation between the measures of employment shortages, the nature of shocks, and subsequent employment adjustments. We group our findings into three categories: (i) characterization of microeconomic adjustment functions; (ii) decomposition of sources of average (aggregate) employment fluctuations; and (iii) description of the role of microeconomic nonlinearities on the dynamic behavior of average employment growth.

The measure of employment shortage undoubtedly is one of the main state variables in any model of adjustment. We simplify our analysis substantially by making this measure the only state variable, besides calendar time and white noise, upon which plants decide by how much to adjust their employment levels at each point in time. Within this limited characterization, we find the following. (i.1) Plants are more likely to react (or

react by more) to large employment shortages than to small ones. For example, on average, about 70 percent of a 10-percent shortage will remain one quarter later, while only 50 percent of a 60-percent shortage will go beyond the current quarter. (i.2) Microeconomic employment adjustment is lumpy and discontinuous. Most distributions of adjustments (conditional on initial shortages) are bimodal: invariably, one of the modes is at zero adjustment. Especially for large initial shortages, the other mode is typically at one (full adjustment). These features are akin to (S, s)-type models.

Mechanically, fluctuations in average (across plants) employment growth over time are due to fluctuations in microeconomic adjustment functions and in the distribution of shortages. More interestingly, these fluctuations are in turn due to aggregate and reallocation shocks, filtered through our self-contained framework encompassing microeconomic adjustment functions and distributional dynamics. With this decomposition in mind, we find the following. (ii.1) Between 55 and 85 percent of fluctuations in U.S. average manufacturing employment growth during the 1972:1–1980:4 period (our sample) is due to fluctuations in the cross-sectional distribution of shortages. (ii.2) Fluctuations in the cross-sectional distribution accounting for the changes in average employment growth almost entirely are driven by aggregate shocks rather than by changes in the distribution of idiosyncratic shocks (reallocation shocks). This conclusion is reached despite the marked countercyclical nature of the second moment of the distribution of idiosyncratic shocks. (ii.3) Similarly, more than 90 percent of the fluctuations in microeconomic adjustment functions accounting for changes in average employment growth are driven by aggregate, rather than reallocation, shocks. Combining both sources of shocks (to distributions and to microeconomic adjustment functions), we conclude that: (ii.4) aggregate shocks account for about 90 percent of fluctuations in average employment growth. (ii.5) Finally, we decompose average employment growth into gross flows of employment creation and destruction. We find that aggregate shocks are also the dominant source of fluctuations in destruction flows, but account for less than half of the fluctuations in creation flows.

Ramey, 1994). On the relative contribution of aggregate and reallocation shocks to the business cycle, the antecedents of the paper include David M. Lilien (1982), Katharine G. Abraham and Lawrence F. Katz (1986), Olivier J. Blanchard and Peter Diamond (1989, 1990), and Davis and Haltiwanger (1990, 1994). The paper also is obviously linked to the long literature on dynamic labor demand models—see Hamermesh (1993) for a comprehensive discussion of the relevant literature.

[2] For the purposes of this paper, plant-level data are preferable to *firm-level* data. While some aspects of plant-level decisions are likely to depend on firm-wide constraints (e.g., credit constraints), there is no doubt that individual plants have independent lives in terms of the shocks that affect them and the associated adjustment. Having a common headquarters is largely irrelevant if individual plants are behaving optimally in response to their own shocks. In this respect, looking at firms creates the problem of looking at an aggregate of more or less independent plants and thereby losing part of the information on which our analysis connecting microeconomics and macroeconomics is built. Nevertheless, it would be of interest to understand the role of firm effects in this context.

The departure of the (nonlinear) microeconomic adjustment functions characterized in (*i*) from the standard linear model (partial adjustment or quadratic adjustment cost model) plays an important role in accounting for average employment fluctuations. We find that: (*iii*.1) a simple parametric version of the aggregate model suggested by the microeconomic nonlinearities described above has a mean square error (MSE) 45 percent lower than that of its linear counterpart; and (*iii*.2) nonlinearities amplify the effect of large aggregate shocks in our sample.

This introduction is followed by Section I, where we describe the basic framework and construct and estimate the mapping from hours-week to establishments' employment shortages. Section II characterizes microeconomic adjustment functions. Section III decomposes the sources of fluctuations in average employment, while Section IV describes the contribution of microeconomic nonlinearities to these fluctuations. Section V concludes.

I. The Basic Framework

In this section we describe the basic framework we use to structure our discussion of the relation between the microeconomic features of the data and aggregate dynamics. In doing so, we distinguish between identities that follow from the definitions we introduce and theory-dependent statements. We present the issues in reverse order. We start with a description of the elements we use to relate microeconomic employment shortages (i.e., the difference between desired and actual employment) and aggregate dynamics. And, we finish by explaining our procedure to estimate microeconomic employment shortages.

A. "Accounting"

We build our framework on a measure of the deviation between desired and actual (from here on, log of) employment at the plant level, which we call the "employment shortage" index z:

$$(1) \qquad z_{it} \equiv e_{it}^* - e_{i,t-1},$$

where the subindices i and t denote plant i and time t, respectively. When describing our

setup as an "accounting" framework, the quotation marks are there to point out that z depends on e^*, which is a *theoretical* construct.

The framework we use as an organizing device has two basic building blocks. The first one captures "locations." We denote the *cross section of plants' employment shortages* immediately before period t's adjustments by $f(z, t)$, so that the fraction of plants with shortages between z and $z + dz$ at time t is (approximately) equal to $f(z, t)dz$. The other basic ingredient of our framework captures "actions." In every time period we group together plants with similar employment shortages before adjustment, and calculate the fraction of the employment gap that is closed, on average, by plants within each of these groups. The resulting function is called the *adjustment function* and is denoted by $A(z, t)$.[3] Thus, the average employment change by plants with shortage z at time t is equal to $zA(z, t)$.

The definitions of the adjustment function and cross-sectional density of employment shortages allow us to relate individual actions to aggregate employment growth. *Average employment growth*, which we denote by ΔE_t, follows directly:

$$(2) \qquad \Delta E_t \equiv \int zA(z, t)f(z, t)\, dz.$$

Mostly to reduce the dimension of the problem, while preserving internal consistency, we use this as our measure of *aggregate employment growth*. It differs from the rate of growth of aggregate employment (in our sample) only in that our measure does not weight plants' employment growth by their size at each point in time. It turns out that, for our sample, this difference is minor; the standard deviation of both growth rates virtually is identical and their correlation is

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[3] It is important to realize that the definition of $A(z, t)$ is silent with respect to the way in which the average adjustment of plants at z takes place. For example, this could be due to all plants adjusting by a small fraction (as in convex adjustment cost models) or by a few plants adjusting fully and most plants remaining inactive (as in nonconvex adjustment cost models). The distinction between these different forms of adjustment functions will be discussed later in the paper.

above 0.96 if no seasonals are removed, while it is over 0.98 if these are removed. Appropriate discussion periodically will remind the reader of this subtle difference and its inconsequential implications as we present our results.

Equation (2) reveals that the connection between fluctuations in the cross-sectional distribution and average employment growth is mediated through the adjustment function.[4] A basic conclusion emerging from the literature on aggregation of (S, s)-type models is that the first moment of $f(z, t)$ is not enough to capture the impact of cross-sectional dynamics on employment, as would be the case with standard linear models (e.g., quadratic adjustment cost model). More generally, it follows from equation (2) that as long as the adjustment function depends on z, aspects of $f(z, t)$ other than its mean influence aggregate dynamics.

For example, if the fraction of the employment shortage that is closed on average grows with the distance between desired and actual employment according to $A(z) = \lambda_0 + \lambda_2 z^2$, with $\lambda_0 > 0$ and $\lambda_2 > 0$, then equation (2) implies that:

$$\Delta E_t = \lambda_0 M_z^{(1)}(t) + \lambda_2 M_z^{(3)}(t),$$

where $M_z^{(i)}(t)$ denotes the ith (noncentral) moment of the cross-sectional distribution of shortages at time t. A slightly more cumbersome expression follows when we develop the noncentral moments in terms of mean and central moments:

$$(3) \quad \Delta E_t = \lambda_0 \mu_z(t) + 3\lambda_2 \mu_z(t)\sigma_z^2(t)$$
$$+ \lambda_2 \mu_z^3(t) + \lambda_2 \sigma_z^3(t)\gamma_z(t),$$

where $\mu_z(t)$, $\sigma_z(t)$ and $\gamma_z(t)$ denote the mean, standard deviation and skewness coefficients of the cross-sectional distribution of shortages at time t. In this simple example, higher moments of the cross-sectional density of

shortages affect the evolution of average employment through mean-variance and variance-skewness interaction terms. We also have that the first moment affects aggregate dynamics in a nonlinear fashion.

A particular plant's labor shortage, z, evolves over time, reflecting the shocks to desired employment and the employment adjustments it undertakes in response to these shocks. Shocks to desired employment can be classified into shocks that are common across plants (aggregate shocks) and plant-specific (idiosyncratic) shocks. To study the impact of both sources of shocks, our framework decomposes the change in a plant's shortage during period t, Δz_{it}, into the sum of three components:

$$(4) \qquad \Delta z_{it} = \Delta E_t^* + v_{it} - \Delta e_{it-1},$$

where $\Delta x_t = x_t - x_{t-1}$, and the first two terms represent a decomposition of desired employment growth, Δe_{it}^*, into an economy-wide average desired employment growth, ΔE_t^*, and a plant-specific (idiosyncratic) shock, v_{it} (which, by definition, has zero mean when averaged across plants for a specific time period), so that:

$$(5) \qquad \Delta e_{it}^* = \Delta E_t^* + v_{it}.$$

Since we are working in discrete time, it is important to make explicit the timing convention for shocks and adjustments. We assume that each period starts with plants' idiosyncratic shocks, continues with the aggregate shock, and ends with plants' adjustments. There is a cross-sectional density of shortages associated with each of these events. The density at the end of the previous period—that is, before any shock takes place at time t—is denoted by $f_1(z, t - 1)$; plants' corresponding shortages are denoted by $z_{i,t-1}^1$. The density that results after the idiosyncratic shock, v_{it}, is denoted by $f_2(z, t)$. Next comes the aggregate shock, E_t^*, which leads to shortages denoted by z_{it} and density $f(z, t)$. At the end of period t, plants adjust employment (by Δe_{it}) and hours (by Δh_{it}). The resulting density is $f_1(z, t)$, and the cycle begins again.

More explicitly, the evolution of the density of shortages during period t is affected by three

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[4] In our specification, fluctuations in the adjustment function also account for part of employment dynamics. We interpret these fluctuations as mostly the result of omitted state variables, and interpret our later finding of small fluctuations in the adjustment function as a validation of our methodology.

inputs. First, the initial density (final density of previous period) $f_1(z, t - 1)$ is convolved with the density of idiosyncratic shocks. To accommodate our empirical findings, we let the latter depend on initial shortages and denote it by $g(v, t|z)$. Thus:

$$(6) \quad f_2(z, t)$$

$$= \int f_1(z - v, t - 1) g(v, t|z - v) \, dv.$$

Second, there is an aggregate shock that shifts all units by ΔE_t^* in state space, yielding $f(z, t)$. Finally, denoting by Z_t and $Z_{1,t}$ the random variables corresponding to $f(z, t)$ and $f_1(z, t)$, we have that $Z_{1,t} = Z_t(1 - J_t)$, where J_t denotes the fraction of its shortage by which a plant adjusts. We denote the density of the latter by $a(j, t|z)$, which satisfies the constraint $A(z, t) = \int ja(j, t|z)dj$, and write down for later use the expression summarizing this last step:

$$(7) \quad f_1(z, t)$$

$$= \int \frac{1}{u} a\left(1 - u, t\bigg|\frac{z}{u}\right) f\left(\frac{z}{u}, t\right) du.$$

B. Measuring Microeconomic Shortages

The previous subsection is accounting, *given* a measure of z. In order to construct an estimate of z, we build on the fact, well known to labor economists, that hours adjust faster than employment. For example, Philip L. Rones (1981) estimates that the average lead time between the downturn in hours and the downturn in employment during a contraction is 5.1 months.[5]

The data used for this study are quarterly, plant-level data on hours and employment for a sample of large, continuously operating plants in the U.S. manufacturing sector for the period 1972 to 1980. The data are a subset of the Longitudinal Research Database (LRD)

(see Appendix A for further discussion of the data) consisting of all establishments in the LRD with nonimputed positive hours and positive employment in *all quarters* from 1972 to 1980. The resulting sample size is around 10,000, which represents between one-fifth and one-seventh of all the establishments in the Annual Survey of Manufactures (ASM). We stop our sample period in 1980:4 because quarterly production worker hours are imputed (i.e., not collected) for all establishments beginning in 1981 in noncensus years.

We assume that the technology and wage schedules are such that if plants did not face costs of adjusting their level of employment, they would always keep the same number of hours per worker. On the other hand, if costs of adjusting employment are larger—at least in the short run—than those of changing the number of hours per worker, then hours per worker will be positively correlated with the degree of plants' shortages.[6] For formalizations of this idea, see e.g., Mark Bils (1987) and Caballero and Engel (1993). In the latter, plants' production functions are Cobb-Douglas in hours per worker and employment. Productivity and demand shocks follow independent random walks. Plants are competitive in the labor market but face a (per-hour) wage curve that is a function of the average number of hours worked. Adjusting average hours is costless (see Thomas J. Sargent [1978] and Matthew D. Shapiro [1986]), yet adjusting employment is not. It follows from these assumptions that a plant always chooses average hours to maximize its current profits, conditional on its current employment level. Comparing the actual employment level with that which would be optimal if employment could be adjusted costlessly leads to expression (8) below.

We summarize this discussion in a simple expression where, when adjustments have already settled at the end of period t, shortages are related to excess hours for each plant i:

$$(8) \qquad z_{it}^1 = \theta_i (h_{it} - \bar{h}_i),$$

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[5] See Hamermesh (1993) for an extensive discussion and further references on the evidence on lead-lag relationship between hours and employment adjustment.

[6] "When Cooper [Industries] had a surge in orders for the computer cables it makes, more than 2,000 workers were asked to work an additional two hours a day, on overtime pay. Only as a last resort has Cooper recently begun to hire. [...]" (*The New York Times*, 1993).

where h_{it} is the (log of) hours per worker in plant i at time t; $\bar{h}_i$ is the sample average of the hours per worker in plant i; and θ_i is a parameter.[7] Since z_{it} differs from z_{it}^1 only in that the latter incorporates adjustment, we have:

$$(9) \qquad z_{it} = \theta_i (h_{it} - \bar{h}_i) + \Delta e_{it}.$$

By obtaining estimates of the θ_is, we can construct estimates of the paths of the z_{it}s using (9). This provides empirical content to the decomposition of employment adjustment presented in the previous section.

Replacing definition (1) in (9), taking first differences of the resulting expression, and rearranging, yields the following:

$$\Delta e_{it} = -\theta_i \Delta h_{it} + \Delta e_{it}^*.$$

In principle, the only unobservable in this equation is the (exogenous) shock Δe_{it}^*. In practice, employment and hours changes are likely to be measured with error—both because of data problems as well as theory problems (e.g., omitted state variables and transitory versus permanent shocks). Considering these factors, we rewrite the previous equation in a standard regression format:

$$(10) \qquad \Delta e_{it} = \text{const}_i - \theta_i \Delta h_{it} + \varepsilon_{it},$$

where ε is an error term corresponding to the exogenous shock Δe_{it}^* and measurement error terms, after removing individual effects.

Estimating θ from equation (10) is likely to yield downward-biased estimates for two reasons. First, since hours are used to accommodate part of frictionless shocks (Δe^*) when employment does not adjust fully, changes in hours and the component of ε due to the frictionless shock are positively correlated. Second, the measurement error in

hours and changes in hours also are positively correlated.

A partial solution to the first problem, which is based on adjustment costs, emerges from the model itself. If plants' employment adjustments are infrequent and large, then we can use the observations of periods where an adjustment occurs, for in those episodes changes in employment and hours should be one order of magnitude larger than ε.[8] We estimate the equation above using only observations with changes that are larger than one standard deviation of the changes in employment and hours in each of our groups (see below).

Solving the first problem does not remove the measurement error bias, however. In order to reduce this problem we run a reverse regression (i.e., with Δh on the left-hand side) using the same observations. Due to the measurement error in employment, this yields an *upward*-biased estimate of θ. It follows that there is a convex combination of the downward-biased estimate of θ, $\hat{\theta}_1$, and the upward-biased one, $\hat{\theta}_2$, that minimizes the mean-squared error of $\hat{\theta}$. Calling this estimator $\hat{\theta}$, we have:

$$\hat{\theta} = \alpha \hat{\theta}_1 + (1 - \alpha) \hat{\theta}_2,$$

where α is chosen to minimize the mean-squared error, under the assumption that measurement error in employment and hours are uncorrelated and have equal variance, and these in turn are equal to the variance of the signals. This configuration of parameters yields a value of α of 0.67 for large samples (more than 200 observations) and a value of α that approaches one as the sample size becomes sufficiently small (fewer than 40).

For the results reported in the main text of the paper, we estimate the values of the θ_i's by pooling the plant-level data for each two-digit industry. Allowing for two-digit variation achieves a reasonable compromise between precision and flexibility. The typical two-digit

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[7] In practice, as noted below, we focus our attention on results based on allowing θ_i to vary by two-digit industry. We also considered a wide variety of alternative specifications including allowing for time variation in θ and seasonal variation in target hours, but the main results did not change. Sensitivity analysis along these and other dimensions is presented in a robustness appendix available upon request.

[8] See the working paper version of this paper— Caballero et al. (1995)—for a more thorough discussion of this approach, and the complications brought about by measurement error.

industry has a large number of observations so that the mean α used in weighting the upper- and lower-bound estimates across industries equals 0.69. The estimated θs are fairly constant across sectors. The mean θ is 1.26; it varies from 0.86 in the petroleum industry to 1.62 in the furniture industry. Replacing these estimates in expressions (8) and (9), we construct a time series of employment shortages for each establishment.

II. Characterizing Microeconomic Adjustment Functions and Heterogeneity

In this section we characterize microeconomic adjustment functions and the evolution of the cross-sectional distribution and its determinants, while in the next section we measure the impact of these factors on aggregate dynamics. All the calculations below use a discretized state space. The shortage index z takes values between -6.0 and 8.0 over an equally spaced grid with partitions of length 0.01.

A. Adjustment

At each point in time, the adjustment function is constructed by dividing by z the average employment growth of those that are at z just before employment adjustments take place, for all $z \neq 0$. The conditional distribution of adjustments, on the other hand, corresponds to the entire histogram of adjustments conditional on, and normalized by, the corresponding z.

The solid line in panel (a) of Figure 1 depicts the average (over quarters) adjustment function. The adjustment functions are smoothed with a cubic spline. We do this to facilitate the exposition. All simulations and decompositions in the following sections are implemented with the actual functions. It is apparent from this figure that the adjustment function is *increasing* with respect to the (absolute value of) microeconomic shortages. As mentioned above, this type of microeconomic nonlinearity is akin to (S, s)-type models, and implies that aspects of the cross-sectional distribution of shortages other than its first moment matter for aggregate dynamics.

Panels (b)–(d) in Figure 1 show the distribution of adjustments conditional on different ranges for employment shortages just before adjustments take place. The horizontal axes represent the fraction of the (absolute) shortage closed (measured as the ratio of actual employment growth to z). To construct these panels, we used the pooled, plant-level data for all periods to generate the distributions depicted. Thus, for example, the bar in panel (d) at the value equal to one on the horizontal axis represents the fraction of observations with the employment deviation range of [0.2, 0.3] that completely closed the gap.

Panel (b) corresponds to situations where initial shortages are small, while the next two panels correspond to situations where initial shortages and excesses of employment are large. Three observations stand out. First, there is always a mode at zero,[9] indicating that a large number of establishments choose not to adjust, even in circumstances where their shortages are large. This evidence supports the hypothesis that there is a nonconvexity in the adjustment technology of individual establishments. Second, as the (absolute value of) shortages get large, a second mode emerges at one. This reflects two aspects of the establishments' adjustment technologies: (a) the adjustment function is increasing, which explains why the second mode emerges more clearly for large shortages; and (b) lumpy and complete adjustments are frequent among plants with large shortages, which suggests increasing returns in the adjustment technologies. And third, although there is substantial dispersion in the distribution of adjustments, the majority of plants adjust in the direction, and within the range, indicated by the model.

Unquestionably, adjustment decisions at the plant level must depend on state variables beyond our measure of shortages. We attempt to gauge the extent of the influence of these

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[9] By zero we mean changes in employment of less than 5 percent *of the shortage*. Of course, this means that the "no-adjustment" category allows for larger, absolute employment changes when (absolute) shortages are larger. Measurement error aside, we think this is a pragmatic normalization.
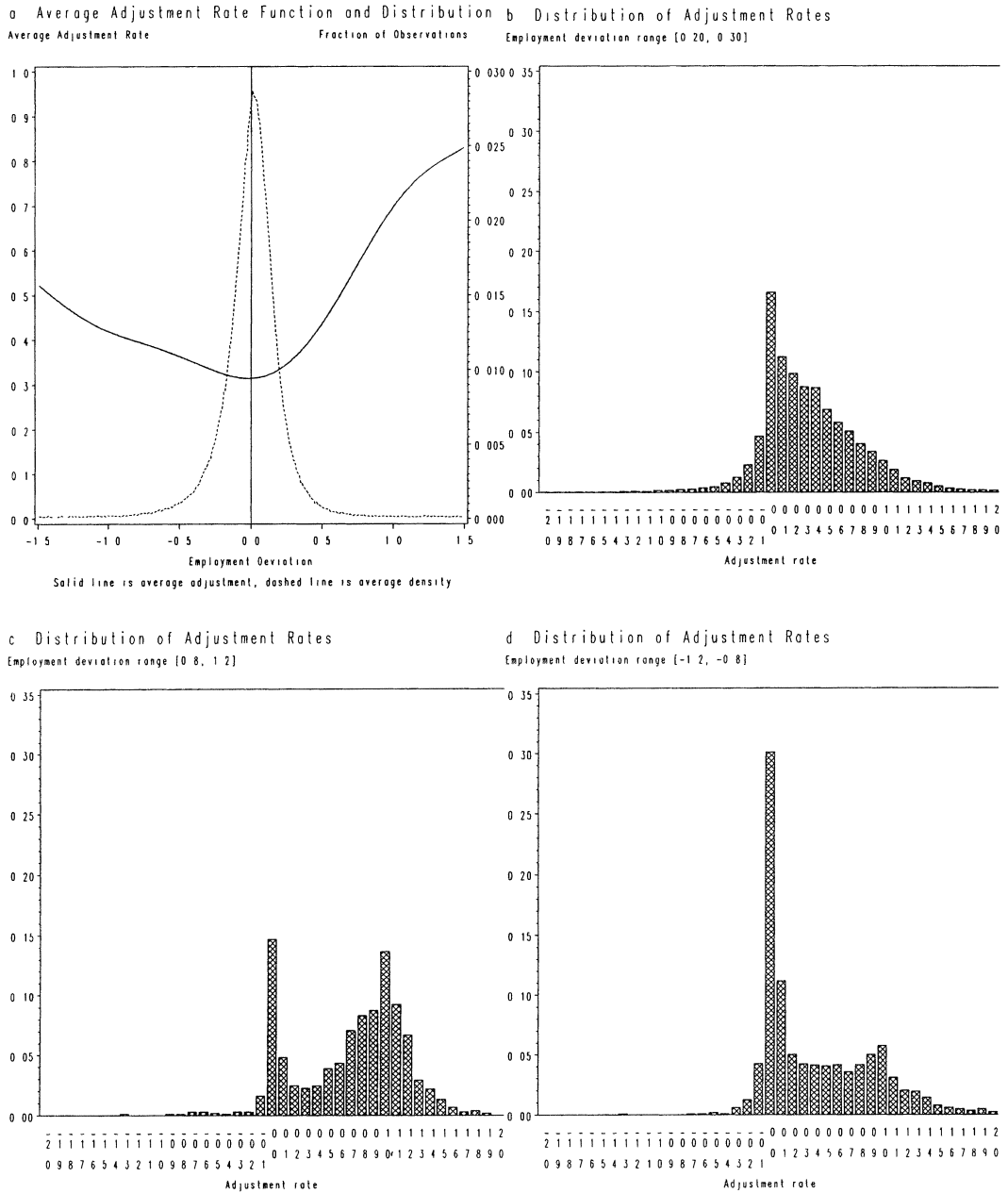
FIGURE 1. RELATIONSHIP BETWEEN EMPLOYMENT CHANGE AND EMPLOYMENT DEVIATION

Source: Authors' calculations using LRD data.

"unobserved" factors by studying the time-series behavior of the adjustment function. Since our data are quarterly and not seasonally adjusted, it is somewhat more revealing to report the path of the adjustment function in two steps. In the first one we show the seasonal

component in isolation, while in the second one we show yearly averages.[10]

Panel (a) in Figure 2 illustrates the seasonal adjustment functions. The curve labeled first quarter in this figure refers to the adjustment function corresponding to the employment changes from the first to the second quarter; the second quarter refers to the changes from the second to the third quarter, and so on. Several conclusions emerge from this figure. First, the adjustment function clearly is increasing with respect to the absolute value of shortages. Second, there is some mild variation across the seasons. For *given shortages,* there is a higher-than-average propensity to destroy jobs during the first quarter; the second quarter shows a substantially lower-than-average propensity to destroy jobs; the third quarter shows slightly higher-than-average propensity to create, while the fourth quarter shows lower-than-average propensities to create and destroy jobs, particularly for establishments with large (absolute) shortages. These patterns are consistent with the observed seasonal properties of aggregate and idiosyncratic shocks. For example, the second quarter's lower destruction is consistent with the fact that second-quarter shocks are more transitory than shocks in other seasons, a fact we document later in the paper. At the same time, aggregate shocks tend to be particularly bad in the second quarter (in our sample, the average aggregate shock during the second quarter is −4%, while the overall average is 0.1%). This latter fact, combined with the transitory nature of shocks, implies that during the second quarter the left arm of the adjustment function should be substantially lower than average, while the right arm may be above or below average.

Panel (b) in Figure 2 selects a few (1972, 1974, 1975, 1979) annual averages of the quarterly adjustment functions, which illustrate the mild cyclical features of the adjust-

ment function. In particular, it shifts up from 1972 to 1975 and then shifts down from 1975 through 1979. The behavior of the adjustment function around the 1974–1975 recession is particularly interesting. The upward shift in the left arm of the adjustment function in both 1974 and 1975 occurred during the sharp downturn in late 1974 and early 1975. The upward shift in the right arm in 1975 is due to the recovery phase of the 1974–1975 recession. The latter is consistent with the implications of standard search models: the high unemployment rate prevailing at the end of the recession facilitates job creation (conditional on the shortages). Quarterly plots of the adjustment function (not shown) reveal that the big surge in destruction occurs in the fourth quarter of 1974 and the first quarter of 1975, while the increase in creation occurs in the last three quarters of 1975.

The bottom line of Figure 2 is clear: *The adjustment function is increasing with respect to the magnitude of plants' deviations between desired and actual employment; it has a mild procyclical/lower frequency pattern, and a mild seasonal pattern probably linked to the transitory nature of seasonal shocks.*

B. *The Cross Section of Employment Shortages*

The cross section of shortages is the endogenous result of aggregate and idiosyncratic shocks filtered by the microeconomic adjustment functions. Empirically, the cross-sectional distribution corresponds to the histogram of shortages at each point in time. Its average is depicted by the dashed line, back in panel (a) of Figure 1, and it shows establishments spend a large fraction of their time within plus/minus 30 percent of their target employment level.

Panel (a) in Figure 3 shows the path of the mean (solid line) and panel (b) shows the path of the standard deviation and skewness of the cross-sectional density of shortages. To reduce the number of figures we show only seasonally adjusted versions. The conclusions also hold for the seasonally unadjusted series. This figure shows that there is substantial movement in the different moments of the cross-sectional distribution which, according to equation (3),

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[10] We report yearly averages rather than quarterly, seasonally adjusted functions to save space. Most of the relevant information is contained in the figures we present. For visual aid, we also smooth the adjustment functions with a cubic spline. Also, notice that given the nonlinearity of the model, using seasonally adjusted data directly may be less appropriate than in the case of linear models.

a Adjustment Rate by Quarter
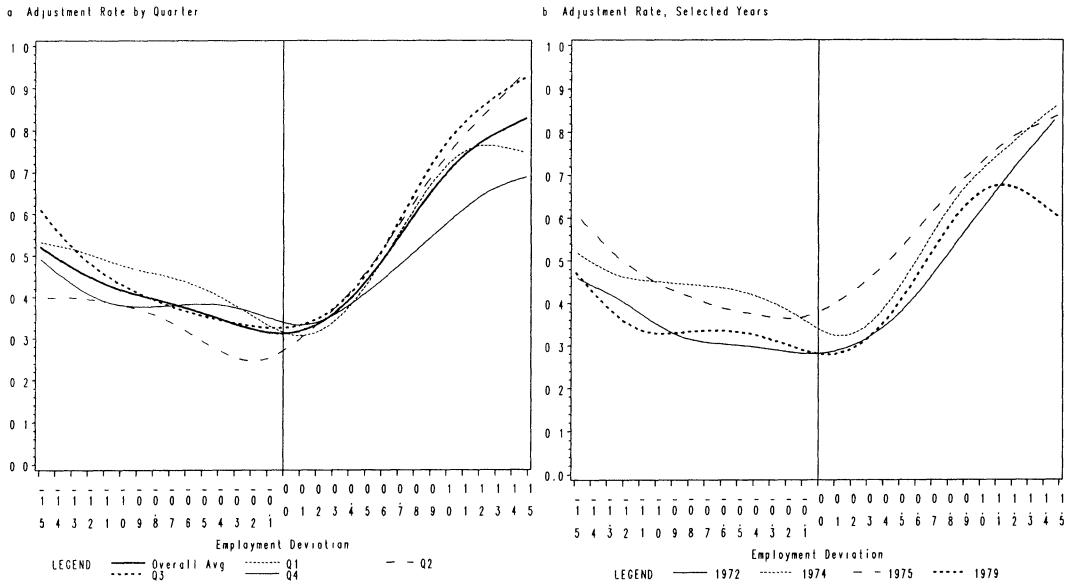
b Adjustment Rate, Selected Years

FIGURE 2. ADJUSTMENT RATES BY QUARTER AND BY YEAR

Source: Authors' calculations using LRD data.

suggests that an important component of aggregate dynamics is missed by looking only at the average shortage.

Given the paths of plants' z_{it}s, we compute their corresponding shocks, Δe_{it}^*s, using equation (1). The path of aggregate shocks, ΔE_t^*s, depicted in panel (a) of Figure 3 (dashed line), shows the path of the average (across plants) of these shocks. This is our definition of aggregate shocks.

At each point in time, the density of idiosyncratic shocks is the histogram of the estimated v_{it}s, which correspond to: $v_{it} \equiv \Delta e_{it}^* - \Delta E_t^*$. The distribution of idiosyncratic shocks plays an important role in shaping the dynamic response of employment to aggregate shocks. In addition to a propagation mechanism, changes in the distribution of idiosyncratic shocks may account directly for fluctuations in average employment growth. This is what is typically referred to as "reallocation" shocks.

Reallocation shocks are usually defined as changes in the standard deviation of the distribution of idiosyncratic shocks. They also can be the result of changes in moments higher than the second, or more subtle

things, such as the presence of serial correlation in idiosyncratic shocks, which would induce correlation between idiosyncratic shocks and the position of plants in state space. We briefly characterize the behavior of some of these factors. Later in the paper we expand the definition of reallocation shocks to include shocks affecting adjustment functions. That is, given exogenous shocks and shortages, establishments may choose to create and destroy more jobs.

Panel (c) of Figure 3 illustrates the paths of the standard deviation and skewness of idiosyncratic shocks. There is no particular pattern in third moments but a clear increase in the second moment during the 1974–1976 period, including the recession and its recovery, and during the second oil shock.

Panel (d) depicts the first-order serial correlation of idiosyncratic shocks, as well as the correlation between these shocks and z_1, the shortages at the beginning of the period. It is apparent that these are nonnegligible, and that they vary over the sample, although these features are likely to arise from measurement error problems (see Caballero et al., 1995).

a. Mean Employment Deviation and Aggregate Shock

b. Higher Moments of Employment Deviation

c. Higher Moments of Idiosyncratic Shocks

d. Properties of Idiosyncratic Shocks
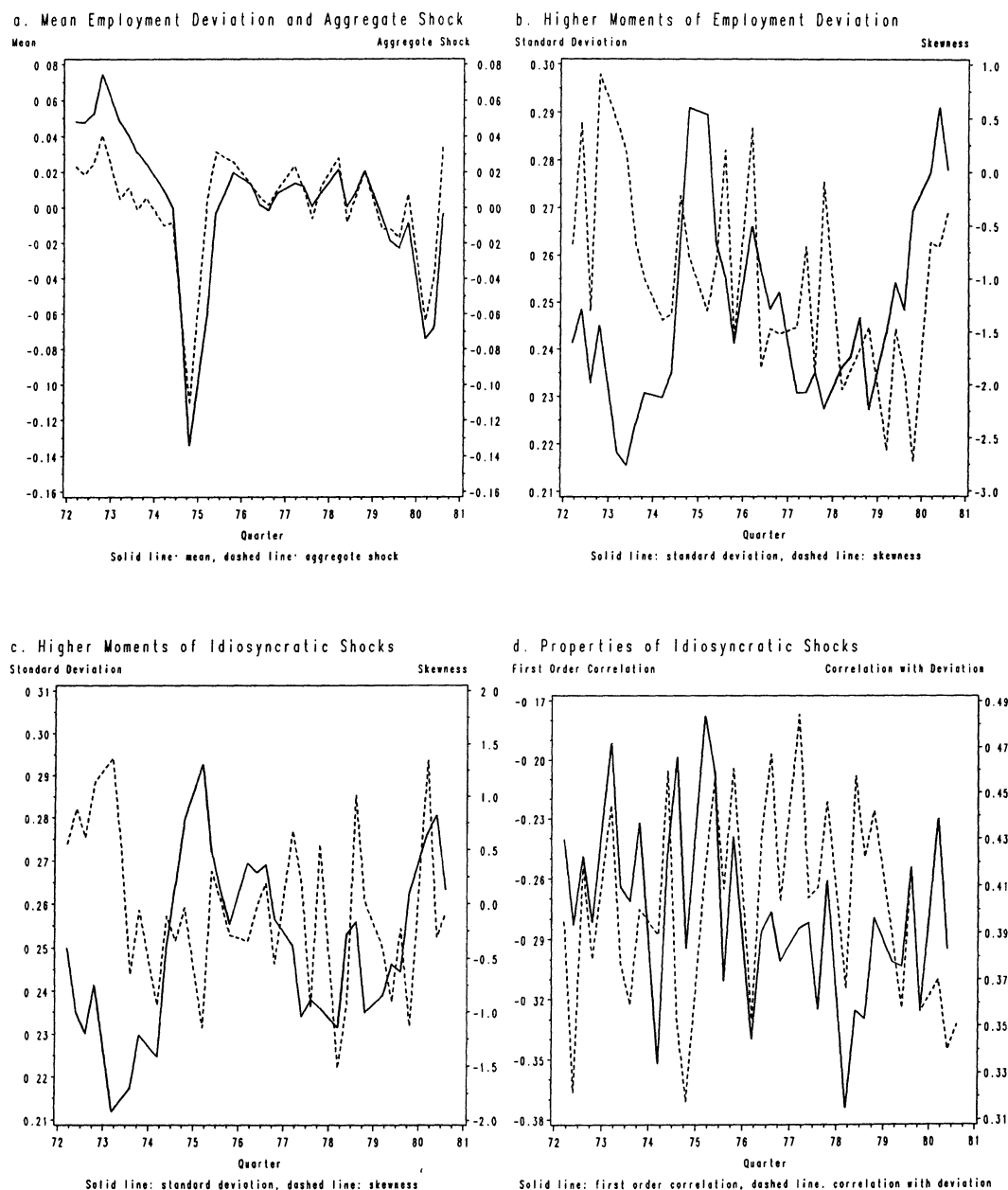
FIGURE 3. MOMENTS OF EMPLOYMENT DEVIATIONS AND SHOCKS (SA)

Source: Authors' calculations using LRD data.

Finally, it is worth pointing out the robustness of our results to standard measurement error problems. In the working paper version (Caballero et al., 1995) we show that measurement error tends to conceal, rather than artificially generate, the features we find. In particular: $(m.1)$ if the adjustment function is smooth and increasing in the absolute value of

z,[11] the minimum value estimated for the adjustment function is upward biased while the maximum is (almost) unbiased. It follows that in this case the measured adjustment function is less increasing than the actual function; its estimate will be upward biased for small (absolute) values of z and close to unbiased for large (absolute) values of z. On the other hand, no bias arises when estimating a constant adjustment function. (m.2) The measured cross-sectional distribution and the distribution of idiosyncratic shocks are the convolution of the true distributions and a measurement error. (m.3) If idiosyncratic shocks are serially uncorrelated, measured idiosyncratic shocks are negatively, serially correlated and negatively correlated with preshock shortages (z^1). The latter correlation decreases (in absolute value) as the magnitude of the variance of idiosyncratic shocks increases. (m.4) The distribution of conditional adjustments is a convolution of the true distribution and a (complicated function of) measurement error. The bias in the location of the conditional distributions of adjustments decreases (to zero) as the absolute value of z increases. Measurement error cannot create a spurious spike at zero (no adjustment) nor at one (full adjustment); rather, it spreads out any spikes.

III. Aggregate versus Reallocation Shocks

Having characterized microeconomic adjustment and the driving forces behind the evolution of the cross-sectional distribution of shortages, we turn to answer two questions our framework is particularly well suited for: what is the relative importance of aggregate and reallocation shocks for average employment fluctuations?; and what is the contribution of the nonlinear features of microeconomic adjustment to the cyclical behavior of average employment growth? We offer an answer to the former, and perennial, question in this section, while we answer the latter in the next section.[12]

We proceed in four steps: first, we decompose fluctuations in average employment growth into those that are due to changes in the adjustment function and those that are due to changes in the cross-sectional distribution of shortages. Second, we split employment growth due to changes in the cross-sectional distribution into growth corresponding to real-location and to aggregate shocks. Third, we split employment growth due to changes in the adjustment function into growth corresponding to reallocation and to aggregate microeconomic adjustment function fluctuations. And fourth, we combine these decompositions to conclude that reallocation shocks have played only a secondary role in accounting for manufacturing employment fluctuations. As a side product of our procedure, we also document that reallocation shocks played a larger role for fluctuations in gross job flows, especially for job creation.

A. Step 1: Employment Fluctuations due to Changes in the Adjustment Function and Cross-Sectional Distribution

Let $A(z, t)$, $A(z)$, and $A^s(z, t)$ denote the actual, overall average, and seasonal average (i.e., a different average for each season) adjustment functions, respectively. Similarly, let $f(z, t)$, $f(z)$, and $f^s(z, t)$ denote the actual, overall average, and seasonal average cross-sectional density of shortages immediately prior to adjustment. We construct employment growth counterfactuals associated with each possible combination of adjustment function and cross-sectional density described above by substituting $A(z, t)$ and $f(z, t)$ in equation (2) by the appropriate combination:

$$\Delta E_t^f = \int z A(\cdot) f(\cdot) dz.$$

For example, the average employment growth series implied by allowing for seasonal var-

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[11] The smoothness requirement is that the adjustment function's derivative be twice differentiable away from zero and convex in a neighborhood of zero.

[12] Early papers in the aggregate versus reallocation shocks debate include Lilien (1982) and Abraham and

Katz (1986). For more recent references, see e.g., Blanchard and Diamond (1989) and Davis and Haltiwanger (1990, 1994).

TABLE 1—DECOMPOSITION OF FLUCTUATIONS IN AVERAGE EMPLOYMENT GROWTH

| | | R^2 | | |
| | | Adjustment function | | |
Cross-sectional distribution		Average $A(z)$	Seasonal average $A^s(z, t)$	Actual $A(z, t)$
Average	$f(z)$	0.00	0.06	0.48
Seasonal average	$f^s(z, t)$	−0.04	0.12	0.52
Actual	$f(z, t)$	0.70	0.87	1.00

Notes: $A(z, t)$, $A(z)$, and $A^s(z, t)$ denote the actual, overall average, and seasonal average (i.e., a different average for each season) adjustment functions, respectively. $f(z, t)$, $f(z)$, and $f^s(z, t)$ denote the actual, overall average, and seasonal average cross-sectional density of shortages immediately prior to adjustment. Employment growth counterfactuals associated with each possible combination of adjustment function and cross-sectional density are constructed by substituting $A(z, t)$ and $f(z, t)$ in equation (2) by the appropriate combination. $R^2 \equiv 1 - \sigma^2(\Delta E^j - \Delta E)/\sigma^2(\Delta E)$.

iations in the adjustment function and no variation in the cross-sectional density is: $\Delta E_t^f = \int zA^s(z, t)f(z) \, dz$.

The components we wish to consider not only interact with each other, but they do so in a highly nonlinear fashion. Anything reminiscent of an Analysis of Variance, therefore, is very difficult. To measure the proximity between the counterfactual series so constructed and the actual average employment growth series, we use the standard R^2 goodness-of-fit measure: [13]

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

Table 1 shows that changes in the cross-sectional distribution of shortages have more impact on average employment growth than variations in the adjustment function. From the entry (2, 2) of Table 1, we infer that seasonal changes (in both the adjustment function and the cross section) account for 12 percent of fluctuations in employment growth; we are interested in splitting the remaining 88 percent between cyclical fluctuations in both sources. The last column of Table 1 shows that when the actual adjustment function is used, 55 per-

cent (48/88) of employment growth fluctuations (not explained by seasonal effects) is accounted for by going from the seasonal to the actual cross-sectional distribution. And from the other end, the last row reflects that about 85 percent of employment growth fluctuations can be explained without the need of cyclical fluctuations in the adjustment function. [14] Thus, changes in the cross-sectional distribution account for at least 55 percent and as much as 85 percent of fluctuations in employment growth. Given our decomposition, the remainder is due to changes in the adjustment function. [15]

B. *Step 2: Decomposing Employment Fluctuations due to Changes in the Cross-Sectional Distribution*

Figure 3c suggests that the path of the standard deviation of idiosyncratic shocks is highly correlated with aggregate shocks. Indeed, this is the case: the correlation between

[13] We note that this R^2 is not bounded from below by zero since there is no restriction of a zero covariance between the predictions and residuals generated from these exercises.

[14] To obtain this number, we first compute the contribution of adjustment function fluctuations, which is (1.00−0.87)/.88. The contribution of the cross-sectional distribution is the complement of this.

[15] Conclusions are extremely similar if we report the R^2s with respect to the rate of growth of aggregate (of our sample) employment instead of average employment growth. The numbers in the first row become 0.00, 0.01, and 0.42; 0.04, 0.14, and 0.053 in the second row; and 0.68, 0.79, and 0.93 in the last row.

these two series in our sample is -0.39. We show below, however, that once the path of the distribution of idiosyncratic shocks is filtered through the cross section of shortages and adjustment functions, *reallocation shocks have almost no impact on net employment fluctuations.*[16]

In order to determine the impact of changes in the distribution of idiosyncratic shocks on fluctuations in average employment growth, we find the cross-sectional distribution that would have resulted immediately before plants adjust—$f(z, t)$ in the notation of equation (2)—under a variety of assumptions for the distribution of idiosyncratic shocks, and then compute the corresponding employment growth. We perform two types of experiments for each of these scenarios: (i) pseudostatic and (ii) dynamic. For the former, in the notation of equation (6), we consider the *actual* $f_1(z, t)$ and substitute the distribution of idiosyncratic shocks by various expressions to capture the impact of changes in the distribution of idiosyncratic shocks on employment fluctuations. For the dynamic experiment, we take $f_1(z, 1)$ as given, but then use equations (6) and (7), together with the actual conditional distributions of adjustments and the corresponding distributions of idiosyncratic shocks, to generate the sequence of cross-sectional distribution of shortages. The advantage of the dynamic approach is that we can look at cumulative effects; its disadvantage is that the effect of auxiliary assumptions and measurement error also accumulate.

Since equations (6) and (7) define identities, both elements in the first row of Table 2

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[16] It is important to emphasize that this does not imply that the process of reallocation is unimportant in accounting for employment fluctuations. The interaction of the nonlinear microeconomic adjustment functions and the cross-sectional heterogeneity with the aggregate shocks yields rich endogenous dynamics of reallocation over the course of the cycle. The idea that aggregate shocks endogenously change the timing of reallocation has been the recent focus in the theoretical literature examining the connection between business cycles and the process of reallocation (see, e.g., Blanchard and Diamond, 1990; Davis and Haltiwanger, 1990; Robert E. Hall, 1991; Caballero, 1992; Dale T. Mortensen, 1992; Mortensen and Christopher Pissarides, 1992; Caballero and Mohamad L. Hammour, 1994, 1996).

TABLE 2—DECOMPOSITION OF EMPLOYMENT
FLUCTUATIONS: REALLOCATION SHOCKS

Idiosyncratic shock distribution		Pseudostatic R^2	Dynamic R^2
Actual	$g(v, t \mid z)$	1.00	0.98
Seasonal average	$g(v, s \mid z)$	0.95	0.94
Average	$g(v \mid z)$	0.93	0.92

Notes: $g(v, t \mid z)$, $g(v, s \mid z)$, and $g(v \mid z)$ correspond to the actual, seasonal, and overall average cross-sectional distribution of idiosyncratic shocks, respectively. For the pseudostatic experiment, in the notation of equation (6), we consider the *actual* $f_1(z, t)$ and substitute the distribution of idiosyncratic shocks by various expressions to capture the impact of changes in the distribution of idiosyncratic shocks on employment fluctuations. For the dynamic experiment, we take $f_1(z, 1)$ as given, but then use equations (6) and (7), together with the actual conditional distributions of adjustments and the corresponding distributions of idiosyncratic shocks, to generate the sequence of cross-sectional distribution of shortages.

should be equal to one in the absence of rounding errors and approximations; the numbers obtained indicate that approximations have a negligible effect. The first column of Table 2 summarizes the pseudostatic results. The second and third rows replace the actual cross-sectional distribution of idiosyncratic shocks by its seasonal and overall average, respectively. The conclusion we obtain from these rows is clear: conditional on the path of the adjustment function, practically all the fluctuations in the cross-sectional distribution *that are responsible for average employment fluctuations* are directly attributable to *aggregate*, rather than to *reallocation,* shocks. The dynamic results support the same conclusion.[17]

C. Step 3: Decomposing Employment Fluctuations due to Changes in the Adjustment Function

The previous step decomposes about three-fourths of average employment growth fluc-

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[17] If R^2s are computed with respect to the rate of growth of aggregate (of our sample) employment instead of average employment growth, we obtain 0.93, 0.90, and 0.93 for the first column, and 0.93, 0.88, and 0.91 for the second column. Again, the basic conclusions remain unchanged.

tuations into aggregate and reallocation shocks. Here, we decompose the remainder into real-location and aggregate *microeconomic adjust-ment function* shocks. One important obstacle in doing so is that contrary to the case of fluc-tuations in the cross-sectional distribution, the model discussed in Section I offers no natural way to identify reallocation and aggregate shocks. Moreover, it is likely that a large frac-tion of these fluctuations simply correspond to specification error resulting from, among other things, omitted state variables. In spite of this, we adopt the following simple convention: we associate reallocation microeconomic adjust-ment function shocks to *symmetric* shifts in the adjustment function relative to the seasonally adjusted average adjustment function.

Based on the above convention, at any point in time, there is a unique decomposition of the nonseasonal component of the adjustment function, $A(z, t) - A^s(z, t)$, into the sum of reallocation, $R(z, t)$, and aggregate, $P(z, t)$, components:[18]

$$(11) \quad R(z, t)$$

$$+ P(z, t) \equiv A(z, t) - A^s(z, t),$$

$$(12) \quad R(z, t) \equiv \tfrac{1}{2}[A(z, t) + A(-z, t)$$

$$- A^s(z, t) - A^s(-z, t)].$$

Applying the above decomposition, we obtain rather stark results. Starting from the last row of Table 1, we can ask how much R^2 increases by adding the reallocational component, $R(z, t)$, to the seasonal adjustment function: the an-swer is about 0.01. Alternatively, we can ask how much R^2 increases by adding the aggre-gate component, $P(z, t)$, to the seasonal ad-justment function: the answer is 0.12. Thus, aggregate shocks account for more than 90 percent of the employment growth fluctua-tions arising from changes in the adjustment function.

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[18] The following decomposition is based on the fact that any function of a real variable taking real values, $g(x)$, can be decomposed in a unique way into the sum of an even function, $g_e(x)$, and an odd function, $g_o(x)$, with $g_e(x) = (g(x) + g(-x))/2$ and $g_o(x) = (g(x) - g(-x))/2$.

D. *Step 4: Putting Things Together*

Combining the above decompositions yields an estimate of the total contribution of aggre-gate and reallocation shocks. The contribution of reallocation shocks clearly is small. Recom-puting the last row of the static exercise in Table 2, now removing reallocation adjust-ment function shocks, we obtain an R^2 of 0.94, while recomputing the second row (also removing reallocation adjustment function shocks) yields an R^2 of 0.96. Figure 4 illus-trates the actual path of average employment growth (solid line) and the path of the same variable when both sources of reallocation shocks (shifts in the distribution of idiosyn-cratic shocks to desired employment and sym-metric shifts in microeconomic adjustment functions) are removed (dashed line). The conclusion is quite clear: *aggregate shocks are the main contributor to net aggregate employ-ment growth fluctuations in our sample.*

Where do reallocation shocks go? Obvi-ously the answer must be to more disaggregate measures of employment flows. In the ex-tended version of this paper (Caballero et al., 1995), we reproduce the analysis of this sec-tion for gross employment flows (job creation and job destruction, in the Davis et al. [1996] jargon). We conclude there that reallocation shocks account for a small fraction of fluctu-ations in job destruction (about 10 percent), but are an important factor for job creation (over 50 percent). In particular, recessions seem to be times when job destruction is hard hit by aggregate shocks, an effect that is mar-ginally reinforced by reallocation shocks. For creation on the other hand, countercyclical reallocation shocks significantly dampen the impact of aggregate shocks on these flows. In conjunction with the nonlinear adjustment function, these comovements account for the significant cyclical differences between job creation and destruction. For our sample, the standard deviation of job destruction is more than twice that of job creation. The greater cy-clical volatility of job destruction is consistent with the findings reported in Davis et al. (1996), who examine the behavior of job cre-ation and destruction for all plants in the LRD (as opposed to the large, continuing plants that are the focus of this study).
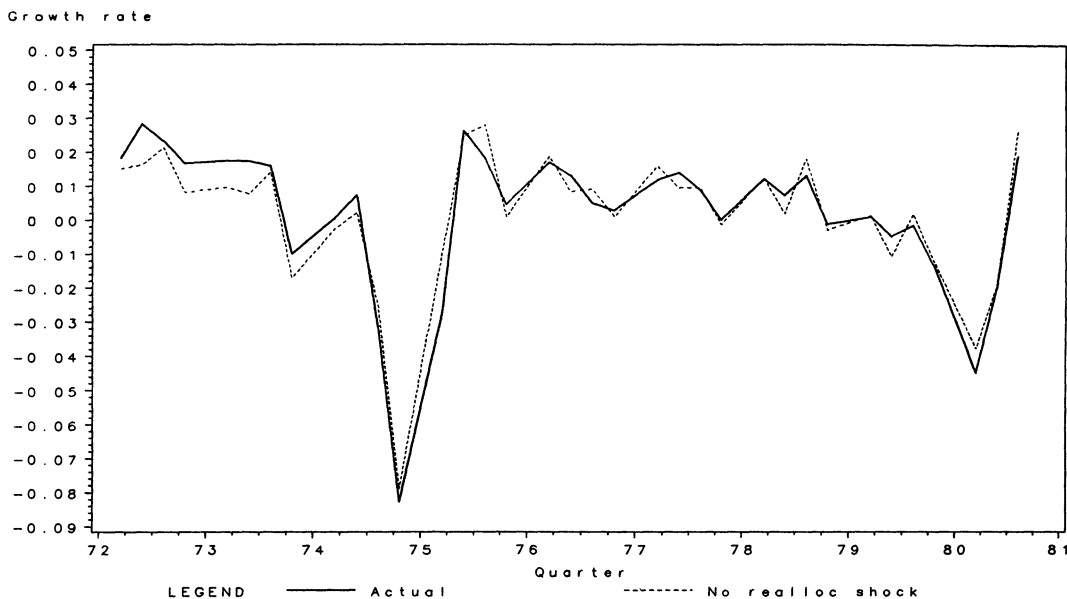
Growth rate

FIGURE 4. THE CONTRIBUTION OF REALLOCATION SHOCKS

Source: Authors' calculations using LRD data.

IV. The Contribution of Nonlinearities

When the adjustment function is constant (in z space), the dynamic behavior of average employment growth is indistinguishable from that of a quadratic adjustment, cost/partial adjustment model (e.g., see Julio J. Rotemberg, 1987). In this case, average employment growth only depends on the first moment of plants' shortages, and aggregating plants' behavior is trivial. However, it follows from Figure 1 in Section II that the adjustment function is *not* linear with respect to z. In particular, plants react more to large employment gaps than to small ones. In this section we go beyond a qualitative appraisal of nonlinearities, and quantify their effect on average employment growth fluctuations.

A. Estimation

We consider a simple family of adjustment functions that captures the qualitative characteristics described above:

$$(13) \quad A(z) = \begin{cases} \lambda_0 + \lambda_1^- |z| & \text{if } z < 0, \\ \lambda_0 + \lambda_1^+ |z| & \text{otherwise,} \end{cases}$$

where λ_0, λ_1^+ and λ_1^- denote nonnegative constants. The main qualitative characteristics of the hazard in Figure 1 are captured when $\lambda_1^+ > 0$ and/or $\lambda_1^- > 0$; the partial adjustment model obtains when $\lambda_1^+ = \lambda_1^- = 0$.

Substituting the adjustment function in (13) for $A(z, t)$ in (2), and allowing for a free constant, leads to:

$$(14) \quad \Delta E_t = c + \lambda_0 M_t^{(1)} - \lambda_1^- F_t(0) M_t^{(2-)}$$

$$+ \lambda_1^+ [1 - F_t(0)] M_t^{(2+)},$$

where $M_t^{(k)}$ denotes the k-th moment of shortages during period t; a super index $^+$ or $^-$ indicates that the corresponding moment only considers plants with positive (respectively negative) shortages; and $F_t(0)$ denotes the fraction of plants with excess employment ($z < 0$) at time t.

TABLE 3—ADJUSTMENT FUNCTION ESTIMATION USING MOMENTS

Parameter	Average employment		Aggregate employment	
	Linear case	Nonlinear	Linear case	Nonlinear
λ_0	0.402	−0.154	0.402	−0.155
	(0.051)	(0.123)	(0.052)	(0.128)
λ_1^+	—	1.30	—	1.31
		(0.31)		(0.32)
λ_1^-	—	1.32	—	1.29
		(0.35)		(0.37)
c	0.002	0.013	0.000	0.012
	(0.002)	(0.013)	(0.002)	(0.014)
$\bar{R}^2$	0.647	0.793	0.637	0.778
DW	1.99	2.22	1.77	2.10

Notes: OLS estimates with 35 observations (1972:2 to 1980:4). The nonlinear case for average employment is based on estimating the equation: $\Delta E_t = c + \lambda_0 M_t^{(1)} - \lambda_1^- F_t(0)M_t^{(2-)} + \lambda_1^+ [1 - F_t(0)]M_t^{(2+)}$, where $M_t^{(k)}$ denotes the k-th cross-sectional moment of shortages during period t; a super index $^+$ or $^-$ indicates that the corresponding moment only considers plants with positive (respectively negative) shortages; and $F_t(0)$ denotes the fraction of plants with excess employment ($z < 0$) at time t. The linear case drops the terms with second moments. The columns labeled aggregate employment repeat the exercise using actual aggregate employment growth as the dependent variable.

Table 3 shows the parameters obtained when estimating (14) using ordinary least squares (OLS), both for the linear (partial adjustment) model and for the nonlinear model. Identifying nonlinearities requires "large" changes, of which there are only a few in the 35 aggregate manufacturing observations we use for estimation. Nonetheless, adding two nonlinear parameters improves the $\bar{R}^2$ from 0.647 to 0.793, reducing the MSE by 45%. Moreover, the qualitative features of the estimated adjustment function are broadly consistent with those observed in Figure 1.

It is instructive at this stage to consider whether our conclusions are affected by our selection of average as opposed to aggregate employment growth as the left-hand-side variable. The answer is no, as is clear from the rightmost two columns of Table 3. If the left-hand-side variable is replaced by the rate of growth of aggregate employment (in our sample), the results are virtually unchanged. A related question is how different is the fit of these models from that of standard ARIMA models. To start this comparison, notice that the linear model presented in Table 3 corresponds to an AR1 with additional information on the current shocks. Instead, if we run a simple AR1 with dummies to capture seasonal shocks, the $\bar{R}^2$ falls

to 0.356; adding further AR and MA terms reaches a peak $\bar{R}^2$, 0.748, at an ARMA(2, 2). If aggregate, instead of average, employment growth is used on the left-hand side, the AR1 with seasonal dummies has an $\bar{R}^2$ of 0.295; adding further AR and MA terms reaches a peak $\bar{R}^2$, 0.652, at an ARMA(3, 3).

B. *Interpretation*

In contrast with linear models with fixed parameters, the nonlinear model we have estimated allows for changes in the responsiveness to shocks over the business cycle. This flexibility can be illustrated by calculating the marginal response of average employment growth to aggregate shocks for the adjustment function considered above (see Appendix B):

(15)   Marginal Response

$$= \lambda_0 - 2\lambda_1^- F_t(0)M_t^{(1-)}$$

$$+ 2\lambda_1^+ (1 - F_t(0))M_t^{(1+)}.$$

From this expression, it is apparent that as long as the λ_1s are nonzero, the marginal response will vary over time. Figure 5 portrays the
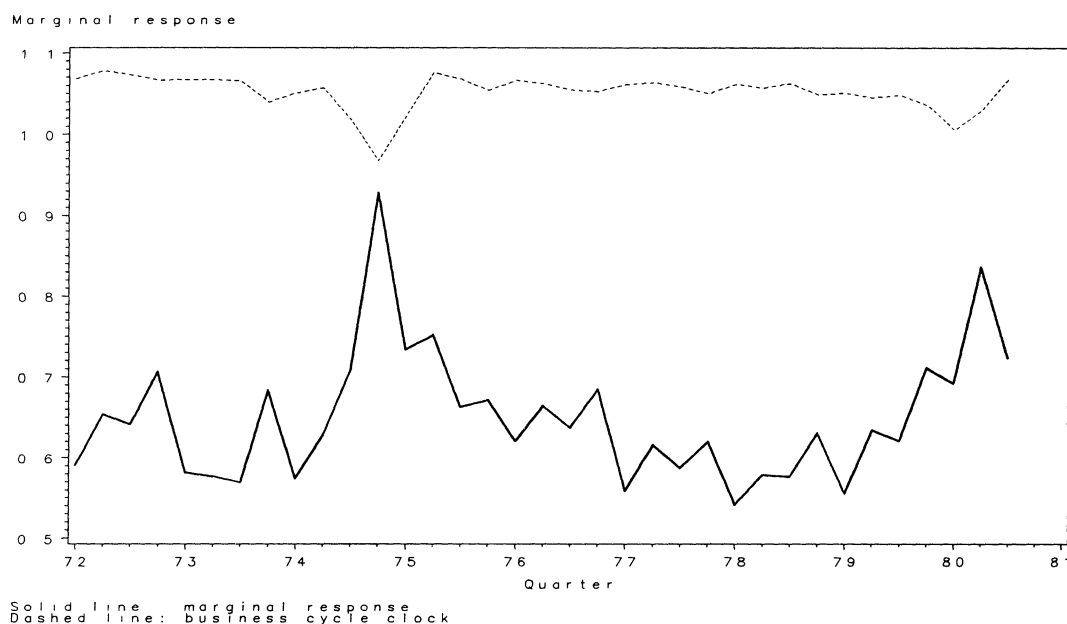
Marginal response

FIGURE 5. MARGINAL RESPONSE OF AVERAGE EMPLOYMENT TO AGGREGATE SHOCK

Source: Authors' calculations using LRD data.

volatile path of the marginal response of employment growth to aggregate shocks over our sample (solid line). It varies as much as 71% and clearly has amplified the effect of large shocks during our sample. The dashed line depicts a business-cycle clock (affine transformation of employment growth).

In order to quantify the contribution of nonlinearities to fluctuations in average employment growth, we decompose the difference between actual and expected average employment growth into the sum of a linear component and a nonlinear component that is equal to zero with a constant adjustment function.[19] Figure 6 shows average employment growth (solid line) and employment growth after subtracting the nonlinear component (dashed line). It is apparent that the impact of the time-varying marginal response is especially large

during the 1974 recession: the decline in employment was 59% larger (8.3% instead of 5.2%) than it would have been in the absence of the nonlinear component.

V. Final Remarks

In this paper, we used a balanced panel of large plants in U.S. manufacturing industries to study microeconomic employment adjustment and its aggregate implications. We used these data to retrace the steps suggested by the literature on aggregation of (S, s)-type models, and in particular, to construct the path of the cross-sectional distribution of deviations between desired and actual employment, as well as the histograms of average adjustments (adjustment functions) at each point in time.

The microeconomic evidence is clearly supportive of the basic implications of (S, s)-type models:[20] substantial inaction, lumpy ad-

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[19] Expected employment growth corresponds to employment growth when the current shock is replaced by its average value over the sample. See Appendix B for details.

[20] See Hamermesh (1989) for an interesting case study documenting microeconomic lumpiness in employment adjustments.

Growth rate

Solid line: actual employment growth
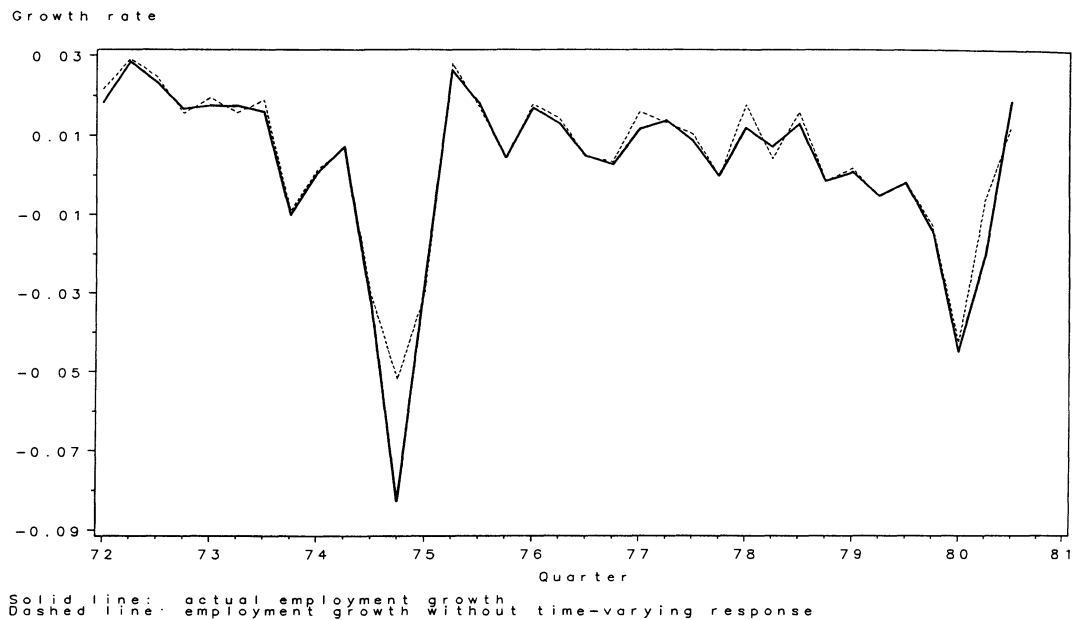Dashed line: employment growth without time-varying response

FIGURE 6. CONTRIBUTION OF TIME-VARYING MARGINAL RESPONSE

Source: Authors' calculations using LRD data.

justments, and an increasing adjustment function. However, we went beyond characterizing microeconomic adjustment functions and used these adjustment functions in conjunction with our estimates of the cross-sectional distributions of shortages and idiosyncratic shocks to study the contribution of several factors to fluctuations in average (aggregate) employment growth.

Our first conclusion from these exercises is that very little of the fluctuations in the cross-sectional distributions *that are reflected in average employment growth fluctuations* can be attributed directly to *reallocation* shocks. This does *not* mean, however, that idiosyncratic shocks are small, or that they do not matter for employment growth fluctuations. Quite the contrary: by far the dominant source of microeconomic employment changes is idiosyncratic shocks, and these play a key role in mapping aggregate shocks into actual employment responses.

These findings lead to our second, and perhaps most important, conclusion. The results in this paper lend support to the view that mi-

croeconomic heterogeneity is important not only for microeconomic issues but also for macroeconomics. Because of the nonlinear nature of microeconomic adjustment, knowing the location of clusters of firms in state space matters for understanding the average response of firms to aggregate shocks. A representative agent framework is ill suited for this task and, therefore, is bound to miss important aspects of employment dynamics. We traced the aggregate effect of the microeconomic nonlinearities we found and concluded that the impact of these is large, especially at times of sharp recessions.

APPENDIX A: DATA APPENDIX

This study exploits the quarterly production worker employment and total production worker hours data in the LRD. It is worth emphasizing that these are the only two variables available at the quarterly frequency in the LRD (most variables are annual, and after 1980 quarterly hours no longer are available). The limited data available at the quarterly

frequency motivates (at least in part) the parsimonious empirical approach we have taken in this paper in characterizing the determinants of desired employment. Quarterly production worker employment data are available for payroll periods covering the 12th day of February, May, August, and November.[21] Quarterly production worker hour data reflect total hours by all production workers for each quarter (January–March, April–June, July–September, October–December). The total hours are all hours worked or paid for, except hours paid for vacations, holidays, or sick leave. Note that the observation on the number of production workers per quarter represents the midpoint of each quarter for which we measure total production worker hours.

The analysis in the paper uses the number of production workers to generate quarterly establishment-level employment growth rates. Quarterly hours per worker are computed as total production worker hours divided by the number of production workers. Establishments that had at least one observation with quarterly hours per worker less than one hour per week or greater than 168 hours per week were excluded. In a given quarter, less than 20 establishments exhibited such outlier behavior. Results generally are not sensitive to the exclusion of such outliers. An extensive discussion of the sensitivity to outliers and other robustness issues is presented in a robustness appendix available upon request.

Since small establishments (less than 250 employees) typically are not in consecutive Annual Survey of Manufactures panels (which last for five years), the typical establishment in our sample is much larger than the typical establishment from a representative sample. In 1977, for example, the average establishment size in our sample is 589 workers, while for all plants the average establishment size is 58 workers. While our sample is not representative, the establishments in our sample constitute approximately 33% of total manufacturing employment in a typical quar-

ter. Further, the time series properties of the quarterly growth rate of production worker employment for all plants and for our sample are very similar. For the sample period 1972:1 to 1980:4, the mean quarterly growth rate for all plants is 0.001, while for our sample the mean is 0.002; the time series standard deviation for all plants is 0.023, while for our sample it is 0.022; and the correlation between the growth rate for all plants and the growth rate from our sample is 0.89.

Given that we restrict our attention to large, continuing plants, this arguably biases against finding that the interaction of microheterogeneity and lumpy employment adjustment matter for aggregate fluctuations. While it is well beyond the scope of this paper to investigate the role of small plants as well as start-ups and shutdowns within the terms of the structure of our analysis, drawing upon the evidence presented in Davis et al. (1996) is suggestive for this purpose. The evidence presented in the latter makes clear that small plants as well as start-ups and shutdowns play a disproportionate role in accounting for observed heterogeneity in establishment-level employment growth rates. For present purposes, start-ups and shutdowns may be particularly important since they represent by definition lumpy, discrete events implying a form of nonlinear microeconomic adjustment that is integral to this type of analysis.

APPENDIX B: MARGINAL RESPONSE TO AGGREGATE SHOCKS

In this Appendix we derive equation (15) in the main text and explain how we calculate the contribution to average employment growth of the time-varying marginal response.

Recalling that $f_2(z, t)$ denotes the density before the aggregate shock of period t, we define:

$$(16) \quad y_t(w) = \int (z + w)A(z + w, t)f_2(z, t) \, dz.$$

It follows that $y_t(w)$ corresponds to average employment growth should the aggregate shock ΔE_t^* be equal to w. Thus, $\Delta E_t = y_t(\Delta E_t^*)$ and the marginal response of aver-

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[21] See Davis et al. (1996) for the procedure used to convert the March data on the number of production workers in the original file to an estimate of the February number.

age employment growth to aggregate shocks is equal to $y_t'(\Delta E_t^*)$.

With $A(z, t)$ defined as in (13), calculating separately the integral in (16) for $z + w < 0$ and $z + w > 0$, leads to:

$$(17) \quad y_t(w)$$

$$= \lambda_0 \int_{-\infty}^{+\infty} (z + w) f_2(z, t)\, dz$$

$$- \lambda_1^- \int_{-\infty}^{-w} (z + w)^2 f_2(z, t)\, dz$$

$$+ \lambda_1^+ \int_{-w}^{+\infty} (z + w)^2 f_2(z, t)\, dz.$$

Calculating $y_t'(w)$ from (17) yields:

$$(18) \quad y_t'(w)$$

$$= \lambda_0 - 2\lambda_1^- \int_{-\infty}^{-w} (z + w) f_2(z, t)\, dz$$

$$+ 2\lambda_1^+ \int_{-w}^{+\infty} (z + w) f_2(z, t)\, dz.$$

Evaluating the expression above at $w = \Delta E_t^*$ and recalling that $f_2(z, t) = f(z + w, t)$, where $f(z, t)$ denotes the cross-sectional density immediately before adjustments take place, we have:

Marginal Response $= \lambda_0$

$$- 2\lambda_1^- \int_{-\infty}^{0} f(z, t)\, dz + 2\lambda_1^+ \int_{0}^{+\infty} f(z, t)\, dz.$$

Equation (15) now follows directly.

To quantify the contribution of the time-varying responses to average employment growth fluctuations, we need to construct a counterfactual where the marginal response of average employment growth fluctuations to aggregate shocks is constant over time (and may vary with z). We do this by decomposing the difference between actual employment growth and employment growth had the aggregate shock been equal to its average value

over our sample, into the sum of a term such that the marginal response at every deviation z is equal to its average value of this response (at z) over our sample and a remainder term. The former term is the "linear" component, and the latter the "nonlinear" one. More precisely, using the notation introduced above and defining:

$$\bar{y}(w) = \frac{1}{T} \sum_{s=1}^{T} y_s(w),$$

we have that:

$$(19) \quad \Delta E_t - y_t(\Delta \bar{E}^*) = y_t^L + y_t^{NL},$$

with:

$$y_t^{NL} = \bar{y}(\Delta E_t^*) - \bar{y}(\Delta \bar{E}^*),$$

and y_t^L defined implicitly in (19).

To calculate the decomposition above, all we need is to calculate $y_t(w)$ for $w = \Delta E_s^*$ ($s \neq t$) and $w = \Delta \bar{E}^*$. We do this using a second-order Taylor expansion for $y_t(w)$ around $w = \Delta E_t^*$ (recall that $y_t(\Delta E_t^*) = \Delta E_t$). The first derivative needed for this calculation was derived above; the second derivative is obtained using a similar argument:

$$y_t''(\Delta E_t^*) = 2\lambda_1^-\ F_t(0)$$

$$- 2\lambda_1^+(1 - F_t(0)).$$

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