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Dynamics of labor demand: Evidence from plant-level observations and aggregate implications ☆

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ABSTRACT

This paper studies the dynamics of labor demand at the plant level to quantify labor adjustment costs. At the plant level, in contrast to time-series observations, the correlation of hours and employment growth is negative while hours and employment growth are about equally volatile. We specify and estimate the parameters of a plant-level dynamic optimization problem using simulated method of moments to match these plant-level observations. Our findings indicate that non-convex adjustment costs are critical for explaining plant-level observations on hours and employment adjustment.

1. Introduction

This paper studies dynamic labor demand at the micro-level. At the plant level, there is about equal adjustment in hours per worker and number of employees, and the co-movement of these variables is negative. In the aggregate time series, which is more commonly used to study labor dynamics and estimate adjustment costs, adjustment is largely in the number of workers rather than hours, and hours growth is positively correlated with employment growth. Given these differences in the pattern of adjustment, estimation of dynamic labor demand using plant-level observations provides new insights into adjustment costs.

Understanding plant-level observations on the labor input requires a model with rich labor adjustment costs. In particular, specifications that ignore labor adjustment costs, such as the standard stochastic growth model, or assume quadratic adjustment costs, as in the linear-quadratic model of Sargent (1978), are unable to match plant-level observations which feature periods of inactivity as well as bursts of adjustment. The importance of non-convexities in adjustment costs for explaining plant-level observations has been pointed out by other researchers, such as Hamermesh (1989), Caballero and Engel (1993), and Caballero et al. (1997).

Our goal is to go beyond those studies by estimating these adjustment costs with a fully specified structural model at the micro-level. To do so, a choice must be made between a particular model of adjustment costs, such as one based on search frictions, or a more general approach that is agnostic with regards to the source of the adjustment frictions.

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Our approach in this paper is to specify a dynamic optimization problem at the plant level with a fairly rich specification of adjustment costs, including both quadratic and non-convex costs of changing the number of workers. Importantly, the estimated parameters include those which govern the process of the exogenous shocks. Since movements in employment and hours jointly reflect adjustment costs and the shock process, it is critical to distinguish these factors.

We estimate the parameters of the plant-level problem with a simulated method of moments procedure using statistics calculated from plant-level data on the number of workers and hours. In particular, we use the standard deviations of employment and hours, the correlation of these two inputs, and the coefficients estimated from a VAR of plant-level employment and hours growth as moments.

For the plant-level data, we find empirical support for adjustment costs which disrupt the production process: the adjustment of the stock of employees entails a reduction in plant-level production. The costs of adjustment are identified from two key features of labor dynamics at the plant level: the standard deviations of hours and employment growth are about the same and the correlation of hours and employment growth is *negative*. Non-convex adjustment costs are needed to match salient features of plant-level adjustment. Importantly, a model with quadratic adjustment costs is unable to reproduce these moments.

The approach taken in this paper contrasts with one that builds directly upon the search and matching framework of Mortensen and Pissarides(1994). A companion paper, Cooper et al. (2007), uses both micro- and macro-moments to estimate the costs of employment adjustment where those costs represent search frictions. That paper finds that micro-non-convexities are important but focuses more on matching hires and separation patterns at the micro-level compared to the moments on hours vs. employment adjustments that are the focus of the current paper. Cooper et al. (2007) do not consider the disruption cost version of the non-convexities that we find are important in matching the rich set of hours vs. employment adjustment moments at the micro-level. In that respect, Cooper et al. (2007) do not provide a structure that can match all of the moments we consider in the current paper. Reconciling the exact form of adjustment costs needed to explain the combined set of micro-moments in the two papers is an area for future research.

The paper begins by reviewing some facts about labor adjustment at the plant level. We then specify and simulate a number of dynamic labor demand models to better understand the mapping from adjustment costs to employment dynamics. Next we present estimates of labor adjustment costs, using the basic facts to guide our empirical exercise.

2. Facts on labor adjustment

Our analysis relies on observations of labor input, employees, and average hours at the plant level. We exploit the Longitudinal Research Database (LRD), a manufacturing plant-level data set for the US. We study a group of plants which are in the sample from 1972 to 1980. Our relatively short time-series sample is due to data limitations. In the LRD, plant-level hours were only collected on a quarterly basis from 1972 to 1980. After 1980, the Annual Survey of Manufactures stopped collecting quarterly hours but continued to collect quarterly employment.

The sample and data we use are identical to those used for Caballero et al. (1997). Like Caballero et al. (1997), we work with a balanced panel and thus do not attempt to jointly study entry and exit along with variations in labor demand. The typical establishment in our sample is much larger than the typical establishment from a representative unbalanced panel. In 1977, for example, the average establishment size in our sample is 589 workers while for all plants in manufacturing the average establishment size is 58. While our sample is not representative of all manufacturing establishments, the establishments we study constitute approximately 33 percent of total manufacturing employment in a given quarter. Further, the time series properties of the quarterly growth rate of production worker employment for all plants and for our sample are very similar.[1]

For these plants the LRD contains information on the number of production workers in each quarter and their total hours worked during the quarter. Quarterly production worker employment are available for payroll periods covering the mid-month of each quarter for the payroll period covering the 12th of the month. Total hours are all hours worked or paid for, except hours paid for vacations, holidays, or sick leave. It is worth emphasizing that the only two variables that are available at a quarterly frequency in the LRD are hours and employment (and again both variables are only available for our sample period). From this information we can measure hours per worker (average) at the plant level for each quarter in our sample.

In what follows, we focus on the growth (log first difference) of hours per worker and employment at the plant level. Focusing on growth rates is natural in this context given the emphasis on adjustment costs. Moreover, the plant-level number of workers varies dramatically across plants given the very skewed nature of the size distribution of employment. Our model and analysis have little to say about the size distribution.

We begin with basic statistics on the growth rate of hours and employment, summarized in Table 1. At the plant level the standard deviations of hours growth and employment growth are about the same. Moreover, hours growth and employment growth are *inversely correlated* at the plant level. As indicated by the standard errors, these moments are

[1] For the sample period, 1972:1 to 1980:4, the mean quarterly growth rate of production worker employment for our sample is 0.002 while for all plants it is 0.001. The times series standard deviation for our sample is 0.022 while for the all plants sample it is 0.023. The correlation between the growth rate for our sample and the growth rate from all plants is 0.89. Additional details on the data set are provided in Caballero et al. (1997).

Table 1
Plant-level moments.

Moments		
$\sigma_{\tilde{e}}$	$\sigma_{\tilde{h}}$	$\text{corr}(\tilde{h}, \tilde{e})$
0.180	0.189	-0.290

All variables are growth rates.

Table 2
Plant-level VAR.

	Estimates	
	$\tilde{h}_{-1}$	$\tilde{e}_{-1}$
$\tilde{h}$	-0.417	0.010
	(0.002)	(0.002)
$\tilde{e}$	0.127	-0.207
	(0.002)	(0.002)

All variables are growth rates. Standard errors are given in parentheses.

tightly estimated in our panel. In what follows, these are the key moments of the plant-level adjustment dynamics that we seek to match.[2]

These statistics are for seasonally adjusted plant-level variation and they change only slightly if the aggregate quarterly time effect (quarterly mean) is removed from the plant-level data. In particular, after removing a full set of aggregate time effects, the standard deviations of hours and employment are respectively 0.179 and 0.188, and the correlation between hours and employment growth at the micro-level is -0.296. The micro-moments are driven almost entirely by idiosyncratic effects: we exploit this in our estimation procedure.

Beyond the most basic statistics, we also consider a parsimonious characterization of the dynamics of plant-level adjustment based upon a two-variable VAR ordered as hours growth ($\tilde{h}$) and employment growth ($\tilde{e}$).[3] We estimate a VAR using quarterly plant-level data, and to control for both seasonal and aggregate cycle effects, we include a complete set of quarterly time dummies (one for each quarter, year observation). This allows us to estimate the relationships using the cross-sectional variation in the time series of plant-level adjustments as distinct from aggregate time-series variation.

The VAR results are presented in Table 2. Here the first (second) row contains the results from the hours (employment) growth regression. The first (second) column contains the coefficient on the lagged value of hours (employment) growth.

Both series exhibit some negative conditional serial correlation. The dependence of hours growth on lagged employment growth is relatively weak, whereas employment growth is positively related to lagged hours growth. Evidently employment growth is led by hours growth.

Putting the basic statistics together yields an interesting pattern at the micro-level. Hours growth leads to employment growth, but contemporaneously, hours growth and employment growth are inversely related. In what follows, these patterns enable us to identify and estimate the structure of adjustment costs.[4]

These plant-level moments contrast rather sharply with the standard characterization of hours and employment growth in aggregate data. If we aggregate our plants, the ratio of the standard deviation of employment growth to the standard deviation of hours growth is 1.81. The correlation of hours and employment growth for the aggregated data is 0.545. Interestingly, from BLS quarterly hours and employment growth rates for manufacturing production workers for the 1972–1980 period, the time-series correlation of hours and employment growth is 0.54 and the ratio of the standard deviations of employment growth to the standard deviation of hours per worker growth is 2.3. This suggests that our sample is representative in terms of its aggregate time-series properties. Also, even over a much longer period 1972–2003, the BLS data exhibit similar patterns: the time-series correlation between employment and hours growth is 0.47 and the ratio of standard deviations is 2.2. We return to the aggregate implications of the model in our concluding comments.

Note that the standard deviations of both aggregate hours growth and aggregate employment growth are considerably lower than the plant-level standard deviations. This reflects the fact that cross-sectional variation in the LRD at the plant level is much larger than the time-series variation.

[2] Cooper et al. (2007) also use the moments from Table 1 but they do not use the moments from Table 2.

[3] Throughout this paper, if x is the level of a variable, then $\tilde{x}$ denotes the growth rate of x.

[4] We are not the first to detect these basic patterns in the micro-data. Caballero et al. (1997) note the pattern of co-movement between hours and employment and use it to motivate their estimation of adjustment hazards.

3. Model

Letting A represent the profitability of a production unit (e.g. a plant), we consider the following dynamic programming problem:

$$V(A,e_{-1}) = \max_{h,e} R(A,e,h) - \omega(e,h) - C(A,e_{-1},e) + \beta E_{A'|A} V(A',e). \tag{1}$$

Here h represents the input of hours by a worker, e_{-1} is the inherited stock of workers and e is the stock of current workers. These variables are all in levels. Note the timing assumption of the model: workers hired in a given period become productive immediately. In (1), β is a fixed discount factor.[5]

For our analysis we assume a Cobb–Douglas production function in which the labor input is simply the product eh. Allowing for market power by the plant, we obtain

$$R(A,e,h) = A(eh)^{\alpha} \tag{2}$$

where the parameter α is determined by the shares of capital and labor in the production function as well as the elasticity of demand.[6]

The function $\omega(e,h)$ represents total compensation to workers as a function of the number of workers and their average hours. This compensation function is critical for generating movements in both hours and the number of workers. We assume that compensation function is given by $\omega(e,h) = e(w_0 + w_1 h^{\zeta})$.

The cost of adjustment function nests quadratic and non-convex adjustment costs.[7] In its most general form, $C(A,e_{-1},e)$ is given by

$$C(A,e_{-1},e) = F + \frac{\nu}{2}\left(\frac{e-e_{-1}}{e_{-1}}\right)^2 e_{-1} + (1-\lambda)R(A,e,h) \tag{3}$$

if $e \neq e_{-1}$. Here F represents a fixed cost of hiring or firing workers. In (3), ν parameterizes the level of the quadratic adjustment costs for the hiring and firing of workers. Note that quadratic adjustment costs are based upon *net*, not *gross*, hires. Finally, $(1-\lambda)$ is the fraction of revenue lost during employment adjustment. This cost represents the disruption of the production and sales processes during periods of labor adjustment.

There are two features of the adjustment cost structure to note. First, the costs are symmetric. Though we can add asymmetric adjustment costs to the model, the moments we have selected to match are symmetric.[8] Second, the costs apply iff there is a net change in the number of employees.[9]

The model allows for two forms of non-convex adjustment costs in which the cost of adjustment is independent of the size of employment change. In one specification, hereafter termed a *fixed cost*, the firm incurs an additive cost of F each period there is a (net) hire or fire. In a second specification, hereafter termed a *disruption cost*, labor adjustment disrupts the production process so that the plant loses a fraction of revenue each time there is a net change in the number of workers.[10]

There are some interesting differences between these versions of non-convex adjustment costs. While the fixed cost does not interact with the state of profitability, the disruption cost does: adjustment is more costly during periods of high profitability. In fact, since new workers are employed within the period, the actual adjustment cost in period t depends on the number of workers in that period. Thus, this is different from most typical non-convex adjustment cost specifications. Still, as demonstrated below, this specification does give rise to inactivity in employment adjustment. Further, we can alter the timing of the model by introducing a time-to-hire assumption, so that workers hired in period t become productive in period $t+1$. In this case, the disruption cost is independent of the flow of new workers in a period.

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[5] Since the estimation is off of plant-level rather than time-series variation, assuming a fixed discount factor is reasonable. We return to this point in our discussion of robustness.

[6] The value of α is given by optimization of capital (K) in the fully specified production function, assuming no adjustment costs of investment:

$$\tilde{R}(A,e,h,K) = (\tilde{A}(eh)^{\alpha_e} K^{\alpha_K})^{(\eta-1)/\eta} - rK$$

where α_e and α_K are the respective labor and capital shares, η is the price elasticity of demand, and r is the rental rate on capital. Maximization with respect to capital leads to the reduced form in (2) where

$$\alpha = \frac{\frac{\eta-1}{\eta}\alpha_e}{1-\frac{\eta-1}{\eta}\alpha_K}.$$

As an example, with η set equal to 5, corresponding to a markup of 25%, and assuming constant returns to scale in capital and labor with $\alpha_e = 0.65$, α is equal to 0.72.

[7] See Hamermesh (1993) for a lengthy discussion of models of labor adjustment.

[8] That is, in principle one could go further to study a VAR which separates job creation and job destruction.

[9] Due to data limitations, we are unable to detect gross hires and fires that leave the number of employees constant. Given the assumption of adjustment costs on *net*, not *gross*, changes in employment, the quit rate plays no role in the optimization problem. Cooper et al. (2007) consider a related framework with a distinction between hires and separations.

[10] Cooper and Haltiwanger (1993) discuss these types of adjustment costs. Caballero and Engel (1999) and Cooper and Haltiwanger (2006) find support for this type of adjustment cost in their studies of capital adjustment.

Table 3a
Structural parameters.

Model	Structural parameters						
	ζ	α	ρ	σ	ν	F	λ
Quad	1.02	0.70	0.70	0.20	0.10		
Fixed	1.02	0.70	0.70	0.20		0.005	
Disrupt	1.02	0.70	0.70	0.20			0.996

Table 3b
Simulated moments.

Model	Moments						
	$\sigma_{\tilde{e}}/\sigma_{\tilde{h}}$	corr$(\tilde{h},\tilde{e})$	$\tilde{h}\tilde{h}$	$\tilde{h}\tilde{e}$	$\tilde{e}\tilde{h}$	$\tilde{e}\tilde{e}$	$C/\Pi\%$
LRD	1.05	−0.30	−0.42	0.01	0.13	−0.21	
Quad	0.35	0.68	0.11	−1.49	0.04	0.26	0.09
Fixed	1.82	−0.11	−0.41	−0.06	0.33	−0.12	0.09
Disrupt	1.10	−0.16	−0.35	−0.15	0.26	−0.04	0.15

Note: $\tilde{e}$ and $\tilde{h}$ are growth rates of employment and hours, respectively. σ_i is the standard deviation of the growth rate of i, $i=\tilde{e},\tilde{h}$. The VAR coefficients are labeled ij, for i & $j \in \{\tilde{e},\tilde{h}\}$, where i is the dependent variable and j is the lagged regressor. The last column displays the average adjustment costs paid as a percentage of profits.

This adjustment cost function yields the following dynamic optimization problem:

$$V(A,e_{-1}) = \max\{V^n(A,e_{-1}), V^a(A,e_{-1})\} \tag{4}$$

for all (A,e_{-1}), where the superscript n refers to the choice of no adjustment of employment and the superscript a refers to adjustment. These options are defined for all (A,e_{-1}) by

$$V^a(A,e_{-1}) = \max_{h,e} R\,(A,e,h)\lambda - \omega(e,h) - F - \frac{\nu}{2}\left(\frac{e-e_{-1}}{e_{-1}}\right)^2 e_{-1} + \beta E_{A'|A} V(A',e),$$
$$V^n(A,e_{-1}) = \max_{h} R\,(A,e_{-1},h) - \omega(e_{-1},h) + \beta E_{A'|A} V(A',e_{-1}).$$

The policy functions indicate the discrete choice of the type of adjustment (a,n) as well as the number of workers and their hours. These policy functions depend on the state vector, (A,e_{-1}).

For a given parameterization of the basic functions, the optimization problem given in (4) is solved using value function iteration to obtain the policy functions. The state space of employment is discretized into a fine grid with approximately 230 points in the relevant portion of the state space. The idiosyncratic shock is assumed to follow a log-normal process with serial correlation ρ and an i.i.d. innovation with standard deviation σ. Using the procedure outlined by Tauchen (1986), this shock process is then transformed into a discrete state space representation, containing 21 points.

We next turn to a discussion of the properties of the policy functions generated by these adjustment costs. The subsequent section presents the estimation results.

4. The economics of adjustment costs

This section provides some insights into the mapping between the adjustment costs and key aspects of dynamic labor demand. Cooper and Willis(2009) provide a detailed discussion of the properties of policy functions for the quadratic and fixed adjustment cost specifications. The discussion here goes further by studying the case of disruption costs ($\lambda<1$) and by looking at particular moments of the data, particularly the variability of hours growth relative to employment growth and the correlation of these two sources of the labor input.

Tables 3a and 3b summarize the moment implications of three models: quadratic adjustment costs (Quad), fixed costs (Fixed), and disruption (Disrupt). These specifications are defined by the parameter restrictions given in Table 3a. The cost of adjustment parameters are chosen so that the total adjustment costs paid by a plant are roughly equal across adjustment cost models. Throughout we set other parameters of the plant-level dynamic optimization problem at levels which are in the neighborhood of the estimates reported in the next section.[11] For the exercises in this section, we deliberately keep all

[11] These are given in Table 4a. These parameters are estimated along with the adjustment costs, as described in the next section.

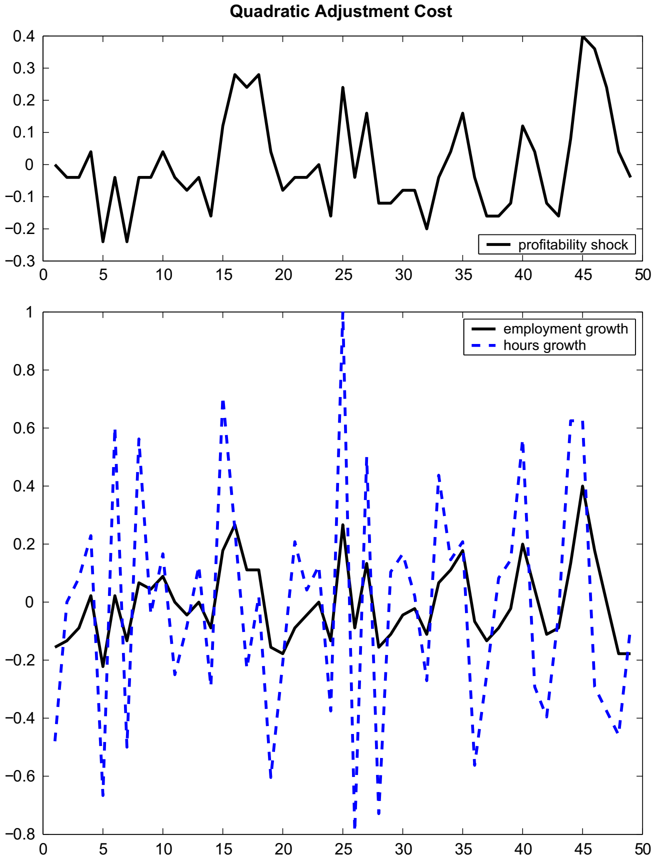

Fig. 1.

parameters the same except for the adjustment costs so that we can gain further insight into the impact of the adjustment costs on the covariance structure of hours and employment growth.

A key issue is the co-movement of hours and employment created by these competing models of adjustment costs. As indicated in Table 3b, the quadratic adjustment cost model creates positive co-movement between employment and hours growth. This reflects the response of these variables to a shock to profitability: both hours and employment rise together at the time of the innovation. Though the adjustment dynamics do create some negative co-movement (as the workforce expands, average hours falls), the response to the innovation drives the positive correlation.

In contrast, the fixed cost and disruption models create negative co-movement. Imagine a plant impacted by a series of relatively small profitability shocks. The plant may initially respond by increasing hours of its workers, keeping the number of employees fixed to avoid the fixed cost of adjustment. But if profitability rises enough, the firm will increase the number of workers *and* cut average hours. This can produce the negative co-movement observed in the plant-level data for these adjustment cost specifications.

A second key moment is the relative variability of hours and employment growth. As indicated in Table 3b, the quadratic adjustment cost model produces a low relative variability, indicating that employment growth varies much less than hours growth.[12] This relative variability is far below the estimate of 1.05 from the plant-level data in the LRD.

In contrast, the fixed cost and disruption models create more variability in employment for the same shock process and the same value of ζ. This increased variability of employment reflects the bunching of job creation stemming from these forms of adjustment costs.

There is also a sharp distinction between the quadratic adjustment cost model and the two non-convex adjustment cost models in terms of the parameters from the simulated plant-level VAR, displayed in Table 3b. In the quadratic adjustment cost model, there is a positive conditional serial correlation for hours growth, whereas the estimate from the LRD data displays negative serial correlation. The quadratic adjustment cost model also displays strong negative dynamics between hours growth and lagged employment growth, where the relationship is basically zero in the data. The other two adjustment cost models are qualitatively similar to the estimates from the LRD. As noted in the Cooper and Haltiwanger

[12] Of course, this also reflects the elasticity of wages with respect to hours and the parameterization of the driving process.

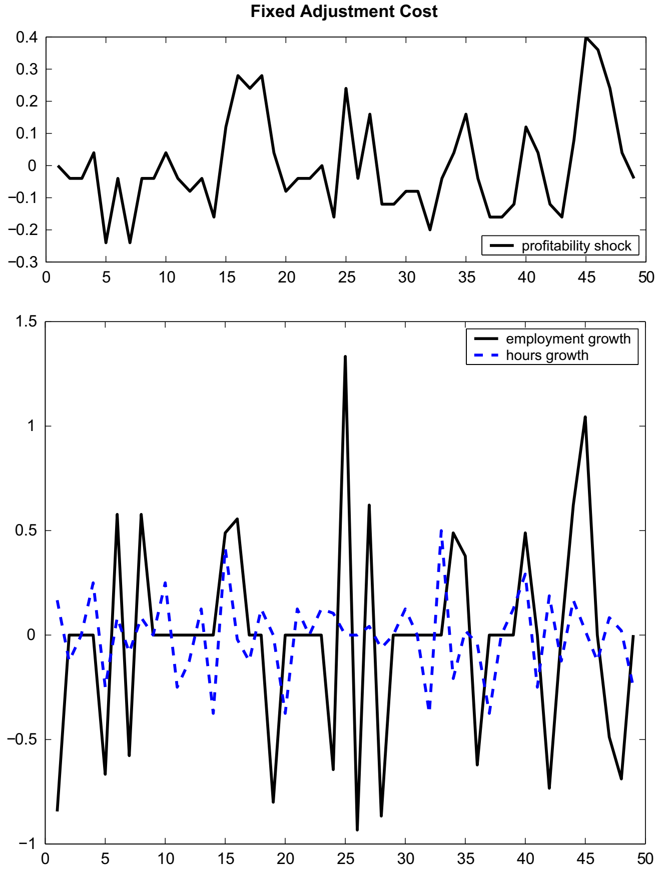

Fig. 2.

(1993) study of capital adjustment, both the fixed and disruption specifications produce bursts of adjustment followed by inactivity, leading to low or negative serial correlation, which contrasts with the positive serial correlation produced in a model of partial adjustment due to quadratic adjustment costs.

The final column in Table 3b is a measure of the size of the adjustment costs paid as a percentage of profits ($C/\Pi\%$), measured as revenues minus labor costs. This was calculated from the simulation of a single plant over 400 periods. The same sequence of shocks is used for each calculation so that they are directly comparable. So, for this parameterization, the adjustment costs in the disrupt case are the largest, at 0.15% of profits.

Further insights into these models of adjustment costs are seen in Figs. 1–3. These figures are created using the parameter values indicated in Table 3a and an identical sequence of shocks.

Fig. 1 illustrates the response of employment and hours growth to profitability variations in the quadratic adjustment cost case. Note that periods of large realizations of the shock lead to growth in *both* hours and employment. Further, hours growth is considerably more volatile than employment growth in the simulation.

Fig. 2 illustrates the fixed cost case. Here, employment growth is frequently zero, with variations in hours used to respond to profitability shocks. There are infrequent bursts of job creation and job destruction, and in some instances, hours growth is of the opposite sign. These movements underlie the moments reported in Table 2b.

Fig. 3 illustrates the disruption cost case. The inaction and negative co-movement from the fixed cost case are present in this specification as well. The variabilities of growth in hours and employment are about the same.

Comparing Figs. 2 and 3 is instructive. Recall that the cost of adjustment in the disruption case depends on the state of profitability: all else the same, adjustment costs are larger if A is higher.[13] Consequently, there are states in which there is adjustment in the presence of fixed costs but no adjustment with the disruption cost specification. Instead, the disruption cost case relies more on hours variation.

[13] The disruption costs also depend on the choice of (e,h), which are not shown in the figure.

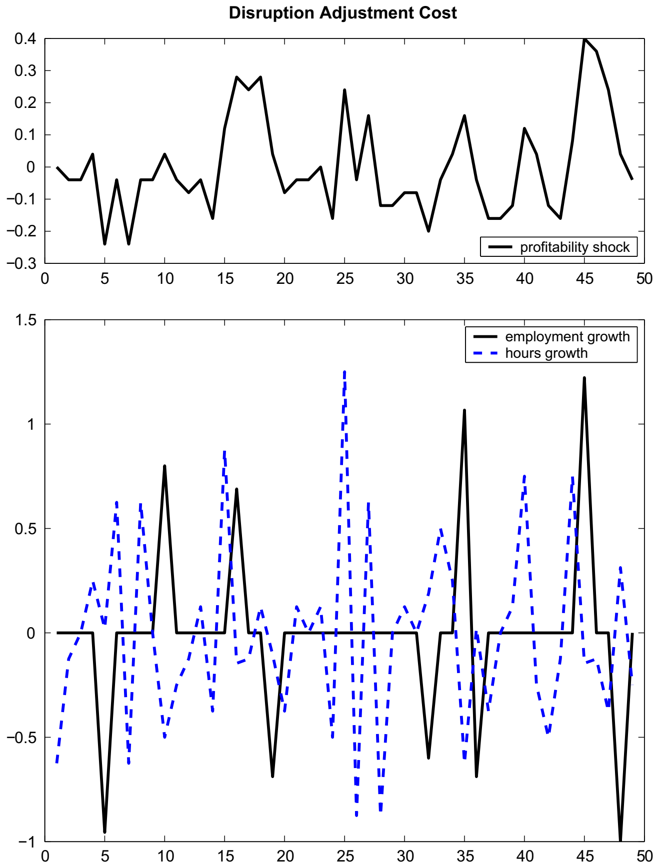

Fig. 3.

5. Estimation of labor adjustment costs

Estimation of the parameters of the dynamic optimization problem follows a simulated method-of-moments procedure. We first discuss the procedure and then turn to results.

5.1. Approach

The estimation entails finding the vector of structural parameters, Θ, which minimizes the weighted distance between moments from the data, M^d, and moments produced from a simulation of the model given a vector of parameters, $M^s(\Theta)$. Thus our estimate of Θ minimizes £(Θ) where

$$£(\Theta) \equiv (M^d - M^s(\Theta))W(M^d - M^s(\Theta))' \tag{5}$$

and W is a weighting matrix.[14]

We solve this minimization problem by simulation since we have no analytic representation of the mapping from Θ to the moments. So, for a given vector Θ, we solve (4) to generate policy functions for employment and hours. Using these policy functions, we create a simulated data set and compute the moments, $M^s(\Theta)$. The data set consists of 1000 plants simulated over 400 periods.[15]

For our analysis, the parameter vector may include all forms of adjustment costs: $\Theta = (\zeta, \alpha, \rho, \sigma, \nu, F, \lambda)$. The first parameter represents the responsiveness of compensation to variations in hours. The second one parameterizes the curvature of the profit function. The third and fourth parameters characterize the AR(1) process for the plant-specific

[14] As discussed in Gourieroux and Monfort (1996), the resulting estimator is consistent.

[15] The results are robust to increasing the number of plants to 10,000 (the approximate size of the LRD panel). The smaller number of plants is chosen to speed computation time. The number of periods in the simulation is set to be over 10 times as long as in the data in order to reduce the impact of initial conditions in the simulation.

Table 4a
Structural parameter estimates.

Model	Structural parameters						
	ζ	α	ρ	σ	λ	F	ν
Quad	8.865 (4.741)	0.03 (0.09)	0.997 (0.002)	0.54 (0.63)	1	0	0.31 (0.93)
Fixed	1.022 (0.0041)	0.79 (0.04)	0.76 (0.02)	0.22 (0.03)	1	0.09 (0.004)	0
Disrupt	1.090 (0.052)	0.64 (0.16)	0.39 (0.02)	0.50 (0.17)	0.919 (0.005)	0	0
DQ	1.013 (0.003)	0.73 (0.03)	0.47 (0.02)	0.49 (0.11)	0.976 (0.020)	0	0.0000209 (0.0000055)

Note: Standard errors in parentheses.

Table 4b
Plant-level moments.

Model	Moments							£(Θ)
	$\sigma_{\tilde{e}}/\sigma_{\tilde{h}}$	corr($\tilde{h},\tilde{e}$)	$\tilde{h}\tilde{h}$	$\tilde{h}\tilde{e}$	$\tilde{e}\tilde{h}$	$\tilde{e}\tilde{e}$	$C/\Pi\%$	
LRD	1.05	−0.30	−0.42	0.01	0.13	−0.21		
Quad	0.56	0.06	−0.004	−0.15	0.002	0.93	−0.0001	26160.4
Fixed	1.07	−0.18	−0.29	−0.07	0.20	−0.08	0.18	2688.4
Disrupt	1.11	−0.29	−0.39	−0.01	0.10	−0.32	2.91	297.7
DQ	1.12	−0.30	−0.39	0.02	0.13	−0.31	0.22	176.3

Note: $\tilde{e}$ and $\tilde{h}$ are growth rates of employment and hours, respectively. σ_i is the standard deviation of the growth rate of i, $i=\tilde{e},\tilde{h}$. The VAR coefficients are labeled ij, for i & $j \in \{\tilde{e},\tilde{h}\}$, where i is the dependent variable and j is the lagged regressor.

profitability shocks.[16] The final three parameters are the adjustment cost parameters. All of our specifications include the first four parameters. We do not estimate all of the adjustment costs simultaneously but rather focus on subsets.

As for the moments, we include the ratio of the standard deviation of employment growth to the standard deviation of hours growth, the correlation of hours and employment growth, and the four VAR coefficients from Table 1b. These moments are at the center of the discussion of labor dynamics and, as indicated by the standard errors of the estimated structural parameters, are responsive to variations in Θ.

Importantly, these moments are constructed by removing time-series variation. For the ratio of the standard deviation of employment to the standard deviation in hours growth and the correlation between employment and hours growth, we use plant-level growth rates where a full set of year-quarter time effects have been removed. In addition, the VAR coefficients from Table 2 are based on a VAR with a full set of year-quarter time effects. Thus the estimation relies on variations across plants.

The weighting matrix, W, is based on the covariances of the moments estimated from the LRD. The covariances are computed through a bootstrap procedure where 1000 samples are randomly drawn from the LRD dataset with replacement, where each sample is the same size as the actual dataset. The six moments are computed from each sample, and the weighting matrix is the inverse of the covariance matrix of the moments across the 1000 samples.[17]

There are some parameters we do not estimate. We set $\beta=0.99$, reflecting our use of quarterly observations. Further, the remaining parameters of the compensation function, w_0 and w_1, were chosen so that steady-state hours were 40 and steady-state employment at each plant was 600.[18]

5.2. Results

Our findings are summarized in Tables 4a and 4b. There are four models estimated. The first three are the respective adjustment cost models, estimated separately.[19] These special cases are included to make clear the significant role of fixed and disruption costs at the plant-level relative to the quadratic adjustment cost model. The fourth model allows for the

[16] Since we have removed all time-series variation from the moments, the model only includes plant-specific shocks.

[17] To indicate the precision with which the moments are estimated, the respective variances of the six LRD moments displayed in Table 2b are (0.000092, 0.000025, 0.000028, 0.000015, 0.000025, 0.000094).

[18] This is the average number of workers per plant in the balanced panel taken from the LRD.

[19] In this table, F is expressed as a fraction of average profits, gross of adjustment costs. Of course, it is treated as a fixed cost in the estimation, as in (4).

presence of both disruption and quadratic costs, we term this the *DQ* model. This joint adjustment cost model was the only combination of the three special cases that resulted in a superior fit of the model to the data.[20]

Here we see the prominent role of disruption costs in matching observations at the plant level, as measured by the relatively low value of $\pounds(\Theta)$ in Table 4b. This specification of adjustment costs alone comes quite close to the observations in many respects. In particular, the disruption case model mimics the negative correlation between employment and hours growth along with the coefficients of the plant-level VAR. It also generates variability in employment growth slightly greater than the variability of hours growth.

The fixed adjustment cost model qualitatively matches many of the moments. In particular, the estimated fixed cost model generates the observed negative correlation between hours and employment growth though it is weaker for the model than in the data. Further, this model also broadly matches the VAR coefficients. Still the fit is not nearly as good as the disruption model, as seen in the value of $\pounds(\Theta)$ in Table 4b for this specification.

The estimated quadratic adjustment cost parameter is very small and the curvature in the compensation function is very large. This specification roughly matches the conditional serial correlation of hours growth, $(\tilde{h}\tilde{h})$, but fails to match the other moments. The quadratic adjustment cost model is unable to generate the negative co-movement of hours and employment growth at the plant level. It also fails to closely capture the relative standard deviations of employment growth and hours growth.[21] A partial explanation for the lack of fit of this moment is the low weight placed on the relative standard deviation compared to weights on the other moments, as determined by the inverse of the variances of the respective moments in the LRD. Note also that for this model, the parameter for the serial correlation of the profitability shock is estimated to be very close to one. This is a sharp contrast to the relatively low serial correlations in the other model and relates to the differences between a convex adjustment cost model, where plants are almost always adjusting employment, and a non-convex adjustment cost model, where there are often longer periods of inaction. The fit is not nearly as good as the fixed model, as seen in the value of $\pounds(\Theta)$ in Table 4b for this specification.

The model allowing for both disruption costs and quadratic costs comes closest to the moments. It is important to note that the parameter for the quadratic adjustment cost is extremely small, 0.00002. However, in comparing this joint adjustment cost model with the disruption cost special case, it is clear that the small amount of quadratic adjustment cost does improve the fit of the simulated moments to the actual data.

In studying these results, recall that the estimation includes the parameters governing the shocks, the curvature of the profit function and the compensation function as well as the adjustment costs. Generally, we find support for a strictly concave profit function $\alpha < 1$ and relatively little sensitivity of compensation to hours variation, ζ near unity. The serial correlation of the plant-level shocks is around 0.50 for the DQ model and significantly less than unity for almost all of the specifications.[22] The standard deviation of the profitability shock is relatively large (particularly in comparison to aggregate time-series variation as described later). Among other things, this exercise indicates that adjustment costs and the driving process must be jointly estimated if the estimation is based on the observed outcomes of employment and hours.

It is instructive to consider the magnitude of these adjustment costs. In comparison to the existing literature, the estimated quadratic adjustment costs are relatively small.[23] The estimate of λ implies a loss of nearly 8% of revenue in the adjustment process for the disrupt case and this falls to 2.4% in the DQ model. From Table 3b, in the DQ specification, the adjustment costs paid in a 400 period simulation are only 0.22% of profits.

From a statistical perspective, the models are all rejected since the reported values of $\pounds(\Theta)$ are quite high. However, in this setting, the moments are calculated from a very large panel data set, implying very small standard deviations of the moments (and a very large W). Given how precisely the micro-moments are estimated from the actual data, virtually any model would be formally rejected with even very modest deviations of the simulated moments from the actual moments. As we have emphasized, the fit of the DQ specification is actually quite good in terms of matching the data moments on both a qualitative and a quantitative basis.[24]

To summarize, there are two conclusions drawn from this analysis:

- both non-convex and quadratic adjustment costs are needed to match observed plant-level labor dynamics
- the disruption case fits the moments better than the specification with fixed adjustment costs.

We now turn to sectoral results to determine if these results are sensitive to disaggregation by industry.

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[20] We also estimated a model with all three adjustment costs. The results were not very different from the combination of the disruption and quadratic adjustment costs. The estimated value of F was not economically significant.

[21] The large value of $\sigma_{\tilde{e}}/\sigma_{\tilde{h}}$ for the quadratic case reflects, in part, the very low estimate of ν.

[22] The exception seems to be the quadratic adjustment cost model in which the parameter estimates are quite different from the other specifications. This leads, as in Table 3b, to negative profits as well. Given the poor fit of the unconstrained model with quadratic adjustment costs, we are not too concerned with these parameter estimates.

[23] Cooper et al. (2007) is an exception and finds relatively small quadratic adjustment costs.

[24] For the models where both convex and non-convex costs are included, we are matching six moments with six parameters. It would thus appear that we have an exactly identified model which should fit the moments perfectly. However, two related factors work against this argument. First, the non-convex models are by construction highly nonlinear so that an exact match of simulated and actual moments is not guaranteed. Second, models are abstract approximations and thus it is too much to expect the model to match the estimated moments exactly. For this reason, we also focus on comparing the fit across models.

Table 5a
Structural parameter estimates.

Model	Structural parameters					
	ζ	α	ρ	σ	λ	ν
Autos	1.006 (0.007)	0.79 (0.11)	0.65 (0.17)	0.53 (0.13)	0.979 (0.008)	0.0000059 (0.0000522)
Steel	1.003 (0.003)	0.71 (0.04)	0.64 (0.06)	0.53 (0.57)	0.991 (0.015)	0.0000031 (0.0000684)

Note: Standard errors in parentheses.

Table 5b
Plant-level moments.

Sector		Moments						£(Θ)
		$\sigma_{\tilde{e}}/\sigma_{\tilde{h}}$	corr($\tilde{h},\tilde{e}$)	$\tilde{h}\tilde{h}$	$\tilde{h}\tilde{e}$	$\tilde{e}\tilde{h}$	$\tilde{e}\tilde{e}$	
Autos:	LRD	1.25	−0.44	−0.42	0.04	0.18	−0.24	
	Est.	1.25	−0.43	−0.38	0.04	0.21	−0.23	6.17
Steel:	LRD	0.95	−0.41	−0.41	0.01	0.16	−0.14	
	Est.	0.94	−0.38	−0.31	−0.02	0.13	−0.19	48.75

Note: $\tilde{e}$ and $\tilde{h}$ are growth rates of employment and hours, respectively. σ_i is the standard deviation of the growth rate of i, $i=\tilde{e},\tilde{h}$. The VAR coefficients are labeled ij, for i & $j \in \{\tilde{e},\tilde{h}\}$, where i is the dependent variable and j is the lagged regressor.

5.3. Sectoral results

The sectoral analysis focuses on plants in two sectors: autos and steel. Tables 5a and 5b summarize our findings. Here we only estimate an adjustment cost model that includes both the quadratic and disruption cost parameters.[25] Qualitatively, the results are quite similar to those reported for all of manufacturing. The estimate of ζ is again near unity implying that compensation is not that sensitive to variations in hours. Further, there is again support for strict concavity of the profit function as well as modest serial correlation of the shocks.

In terms of the adjustment costs, we again see that disruption costs are present along with relatively small quadratic adjustment costs. Interestingly, these disruption costs are more prominent for autos than steel. The higher disruption estimated for autos is partially driven by the substantially higher standard deviation of employment growth relative to hours in autos relative to steel.

Finally, the sector specific models appear to fit much better. This reflects two factors. First, there is more flexibility here in that the parameters are allowed to be sector specific and thus we can fit the moments better. Second, the sectoral moments are not as precisely estimated from the data as there are obviously fewer plants in a sector relative to all of the plants. This reduction in precision is reflected in the weighting matrix, W, used to compute £(Θ). Overall, though, the results at the sectoral level are quite similar to those for the U.S. manufacturing panel.

6. Aggregate implications

In this section, we study the aggregate implications of our model. As noted earlier, the aggregate moments from the LRD are quite different from the plant-level observations. This leads us to inquire whether the model estimated using plant-level observations can, through smoothing by aggregation over heterogeneous plants, produce the moments observed in aggregate data. The first sub-section studies this question and indicates that we can mimic some but not all of the aggregate moments using estimates from the DQ specification. The second sub-section explores how well we can match the aggregate moments by variations in plant-level adjustment costs.

6.1. Smoothing by aggregation

The time-series moments obtained by aggregating over the plants are given in Table 6. The stark contrast between time-series and plant-level variation in the LRD is evident from comparing Tables 1,2 and 6.

[25] As in the overall manufacturing estimates, the model with fixed costs did not perform as well and hence is not shown.

Table 6
Time-series moments.

Model	Moments					
	$\sigma_{\tilde{E}}/\sigma_{\tilde{H}}$	$\text{corr}(\tilde{H},\tilde{E})$	$\tilde{H}\tilde{H}$	$\tilde{H}\tilde{E}$	$\tilde{E}\tilde{H}$	$\tilde{E}\tilde{E}$
LRD-agg.	1.81	0.55	0.06	−0.08	0.56	0.40
		Aggregation without Aggregate Shocks				
DQ	0.32	−0.07	−0.43	0.06	0.00	−0.35
		Aggregation with Aggregate Shocks				
DQ	0.30	0.26	−0.20	−0.44	0.02	0.23

Note: $\tilde{E}$ and $\tilde{H}$ are growth rates of aggregate employment and aggregate hours, respectively. σ_I is the standard deviation of the growth rate of I, $I=\tilde{E},\tilde{H}$. The VAR coefficients are labeled IJ, for I & $J \in \{\tilde{E},\tilde{H}\}$, where I is the dependent variable and J is the lagged regressor.

In particular, for the aggregate time-series moments the ratio of standard deviations of the growth rates, $\sigma_{\tilde{E}}/\sigma_{\tilde{H}}$, is much higher than at the plant level. Further, the correlation of hours and employment growth is positive for the aggregate time series but was negative at the plant level.

The question is whether the models estimated using plant-level data can reproduce these time-series moments. To study this question, we report two additional simulations in Table 6. First, we aggregate over our heterogeneous plants to study the effects of smoothing by aggregation. This is the section of Table 6 labeled "Aggregation without Aggregate Shocks."

Second, we supplement our simulated environment by adding in aggregate shocks at the plant level and then aggregating over the plants using exactly the same procedure as we employed in working with the LRD. This is the section of Table 6 labeled "Aggregation with Aggregate Shocks."

To be specific, for the estimated adjustment costs in the DQ case, an aggregate source of variation has been introduced through a common component in A, the profitability shock. The process for the shocks $(\rho_A, \sigma_{\epsilon_A}) = (0.95, 0.05)$ is chosen so that the model reproduces the basic serial correlation and standard deviation from aggregated (log) employment.[26] Note that for all of the adjustment cost specifications, the standard deviation of the aggregate time-series shocks is considerably less that the cross-sectional variation.

Since we have identified the adjustment cost parameters and other relevant micro-parameters from the cross-sectional variation, adding aggregate shocks in this manner allows us to evaluate how closely we can match the aggregate moments through the smoothing over heterogeneous plants with and without aggregate shocks. A primary item missing is that wages and interest rates do not respond to the aggregate shocks. We comment further on this point below.

The results are summarized in Table 6. The smoothing by aggregation effect alone reduces the variability of employment relative to hours from 1.05 in the plant-level data to 0.32. In addition, while the aggregation does not change the sign of the correlation between hours and employment, it is now only −0.07 rather than −0.30 reported for the plant-level data.

From the next sub-panel, by introducing aggregate shocks and then aggregating, a different pattern of variation in hours and employment growth emerges relative to the model without aggregate shocks. Now we see that the correlation between hours and employment is positive, as in the aggregate time series from the LRD. The relative standard deviation of employment to hours seems unaffected by the introduction of the aggregate shocks.

Thus, the presence of the aggregate shocks combined with the aggregation across heterogeneous units switches the sign of the correlation in the model and brings it closer to the time-series data. Evidently, the common shock effects outweigh the substitution between labor inputs at the plant level.

As for the VAR coefficients, for the model with common shocks, these coefficients move in the direction of those found in the actual aggregate data. The $\tilde{e}\tilde{e}$ coefficient was negative in the plant-level data and for the estimated model. The time-series counterpart, the $\tilde{E}\tilde{E}$ coefficient, is positive in the data and also much larger for the models than in the plant-level data once aggregate shocks are added.

Smoothing by aggregation and the presence of common shocks is clearly a factor that can help reconcile differences in micro- and macro-moments. However, the micro-models that best fit the micro-moments do not fully capture the aggregate movements. In the next section, we explore a calibration sensitivity analysis to shed further light on these issues.

6.2. *Are there adjustment cost parameters that match the macro-moments?*

In this section, we conduct a calibration exercise that searches for parameterizations of the adjustment costs that yield aggregate moments that match the actual moments. Our motivation for this calibration exercise is as follows. A common finding in the literature is that a quadratic adjustment costs specification fits the aggregate data reasonably well. In fact, from Table 3b, the quadratic adjustment cost model has an important features of the aggregate data: hours and employment growth are positively correlated.

[26] This is aggregate employment growth from the BLS manufacturing employment from 1972 to 1980. We match this series by aggregating over simulated choices at the plant level using the estimated parameters of the disruption case reported in Table 3a.

Table 7
Alternative adjustment cost parameters.

Model	Parameters		Moments					
	λ	ν	$\sigma_{\tilde{E}}/\sigma_{\tilde{H}}$	$\text{corr}(\tilde{H},\tilde{E})$	$\tilde{H}\tilde{H}$	$\tilde{H}\tilde{E}$	$\tilde{E}\tilde{H}$	$\tilde{E}\tilde{E}$
LRD-agg.			1.81	0.55	0.06	−0.08	0.56	0.40
Disrupt	0.992		1.72	0.33	−0.23	−0.12	0.41	−0.24
Quad		0.0064	1.81	0.59	−0.34	−0.15	0.02	0.03
DQ	0.996	0.0033	1.76	0.53	−0.25	−0.17	0.23	−0.06

Note: $\tilde{E}$ and $\tilde{H}$ are growth rates of aggregate employment and aggregate hours, respectively. $\sigma_{\tilde{I}}$ is the standard deviation of the growth rate of I, $I=\tilde{E},\tilde{H}$. The VAR coefficients are labeled IJ, for I & $J\in\{\tilde{E},\tilde{H}\}$, where I is the dependent variable and J is the lagged regressor.

In this section we ask: is there a specification of the quadratic cost model in this context that captures the aggregate moments reasonably well? More generally, we want to know whether there are parameterizations involving either convex or non-convex adjustment costs (or both) that can match the actual aggregate moments.

To provide some discipline on this exercise, we start with the disruption case from Table 4a. For this calibration exercise we consider variations in these the adjustment cost parameters, keeping all other parameters (e.g., shock processes and elasticities) the same as those for the disruption model estimated from the plant-level data. We also specify the same aggregate shock process as in the previous sub-section. We search across the adjustment cost parameters (ν,λ) for the values that yield the best matches to the aggregate moments. In doing so, we use an identity matrix for W.

Before proceeding, we emphasize that this exercise is an exploratory sensitivity analysis rather than an alternative estimation exercise. Estimating the structural adjustment cost parameters using plant-level moments is preferable on many grounds. For one, these moments are much more precisely estimated. For the other, the plant-level moments we use for estimation abstracted from aggregate variation and as such we could avoid the complexities of the forces alluded to above that influence the aggregate moments (these include smoothing by aggregation, time-series variation in factor prices, frictions that are a function of aggregate fluctuations, etc.). Still, in spite of these limitations, we regard this calibration exercise as interesting because it potentially sheds light on the relationship between the results in this paper and the literature that estimates or calibrates adjustment costs using aggregate data only. Moreover, one might think of the parameterization of adjustment costs for a macro-model somewhat different than that for a micro-model – that is, adjustment costs in a macro-model might be specified to encompass forces that generate smoothing in the aggregate.

Our findings are summarized in Table 7 where the rows refer to alternative adjustment cost parameterizations. The specification which fits the aggregate moments best is $(\nu=0.0033,\lambda=0.996)$. Relative to the best fitting model for the plant-level data, this specification entails larger quadratic adjustment costs (by a factor of 100) and smaller disruption costs. Still, these adjustment costs are relatively small. Further, the model is still not capable of capturing the full dynamics of hours and employment, particularly the positive $\tilde{E}\tilde{E}$ coefficient.

Interestingly, the model with quadratic adjustment costs alone also is capable of matching both the relatively volatility and the correlation between hours and employment growth in the aggregate data. This specification too fails to capture the dynamics between these variables. It is worth noting that the magnitude of ν in the model with quadratic adjustment costs alone is still very small relative to the magnitude of quadratic adjustment costs that have been used in the empirical literature to capture aggregate fluctuations. Part of the reason for this is likely that we focus on a substantial number of aggregate moments while the literature focuses mostly on the dynamics of employment itself (so the $\tilde{E}\tilde{E}$ coefficient gets much more weight in the existing literature).

7. Conclusions

This paper provides evidence on the nature and significance of labor adjustment costs. Based upon our results, the principle cost of labor adjustment is the disruption of the production process. These costs are needed to match plant-level observations on the covariance structure of hours and employment growth. For plant-level data, quadratic adjustment costs do not appear to be significant. Put differently, a model with only quadratic adjustment costs yields micro-predictions that are very much at odds with the micro-data. A model with fixed adjustment costs does substantially better than a quadratic model but does not match the plant-level data as well as a model which combines disruption costs with (a little bit of) quadratic adjustment costs. The finding that non-convex adjustment costs are needed to match plant-level observations is consistent with the evidence presented by Hamermesh (1989) and the summary of plant-level behavior in Caballero et al. (1997).

While our specification with both convex and non-convex adjustment costs nests the models in much of the literature, there are additional variants which deserve mention. First, in some of the recent literature, stochastic adjustment costs are introduced, following Rust (1987). Stochastic adjustment costs are in our disruption model since the total cost of adjusting will be random due to the profit shocks – periods of high profit shocks will be periods of high disruption costs. However, we do not consider the disruption parameter (or other adjustment parameters) to be stochastic. In the model, the micro-heterogeneity reflects the rich distribution of idiosyncratic profit shocks while in some of this recent literature all of the micro-heterogeneity stems from idiosyncratic draws from the adjustment cost distribution. While heterogeneity from both sources are likely interesting and some of these differences are technical details, the micro-evidence in this paper and the related literature provides overwhelming evidence of a large variance of persistent idiosyncratic profit shocks.

The empirical approach taken in this paper is to focus on cross sectional rather than time series variation. One virtue of exploiting the idiosyncratic variation across plants is that general equilibrium effects can be neglected. That is, the first-order effects from general equilibrium considerations presumably result from aggregate shocks that impact wages and interest rates. By exploiting cross-sectional variation, we have effectively abstracted from these variations.[27]

As an extension of our framework it is natural to consider the aggregate implications of our estimated model. We make only limited progress on considering aggregate fluctuations in the current paper in showing that smoothing by aggregation as well as the role of aggregate shocks helps make the implied macro-variation in hours and employment from our micro-based estimates closer to that found in the data. Our analysis on this is incomplete on a number of dimensions. First, we do not consider general equilibrium considerations. Second, we do no consider the broader question of the aggregate implications of the micro-non-convexities we have identified. Cooper et al. (2007) consider a related model where they include aggregate shocks and take into account the relationship between movements in aggregate wages and aggregate shocks. They show that the type of non-convexities we emphasize in the current paper is important for accounting for aggregate fluctuations in unemployment and vacancies. Still there remains much work to be done to determine the model that matches both micro- and macro-moments on labor adjustment and in turn to consider the aggregate implications of such a framework.

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[27] While we think it is reasonable to argue that the variation we are exploiting here is driven by the idiosyncratic shock distribution (as opposed to aggregate shocks), an argument can be made that some aspects of the idiosyncratic variation we are exploiting is actually driven by aggregate shocks. That is, in principle, aggregate shocks may impact not only the first moments of the hours and employment growth rate distributions but higher moments as well. Following this logic, the changes in wages and interest rates induced by aggregate shocks may in turn have an impact on higher moments of the plant-level distributions. This issue is one we will address in future research. We are grateful to Victor Aguirregabiria and Simon Gilchrist for discussions on this point.