LABOUR ADJUSTMENT COSTS: ESTIMATION OF A DYNAMIC CHOICE MODEL USING PANEL DATA FOR GREEK MANUFACTURING FIRMS

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Abstract

In this paper we estimate a dynamic structural model of employment at the firm level. Our dataset consists of a balanced panel of 2790 Greek manufacturing firms. The empirical evidence of this dataset stresses three important stylized facts: (a) there are periods in which firms decide not to change their labour input and stay inactive, (b) there are periods of large employment changes (lumpy nature of labour adjustment) and (c) the commonality is employment spikes to be followed by smooth and low employment growth periods. Following Cooper and Haltiwanger (2006) we consider a dynamic discrete choice model of a general specification of adjustment costs including convex, non-convex and “disruption of production” components. We use a method of simulated moments procedure to estimate the structural parameters. Our goal is to investigate the nature of the labour adjustment process at the firm level for Greek data.

JEL codes: C02, C13, C15, C44, C51, C61, C63, C81, J01, D21

Key Words: labour adjustment costs, dynamic discrete choice model, Method of Simulated Moments.

1. Introduction

“The vast literature on dynamic factor demand has been organized around the concept of costs of adjustment. The standard assumption has been that these costs are convex and symmetric… [This] convenient approximation detracts from our ability to provide useful discussions of macroeconomic behavior and microeconomic policies… An important first step will therefore be to discover the correlates of the structures of adjustment costs in order to learn how widespread each potential [structure] of these costs is…”

Hamermesh and Pfann (1996, p. 1289)

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1.1 Motivation

Many studies so far have tried to establish a universal explanation for the significant increase and the persistence of European unemployment. Commonly referred to as the *Eurosclerosis* problem (a term introduced by Giersch, 1985), researchers have above all focused on the high degree of labour market rigidities, since such reasoning seems to support the widening gap between unemployment in Europe and the United States.

Labour market rigidities are a decisive factor of the European unemployment problem since they seem to offer an explanation of the problems observed in Europe. To be precise, rigidities are an appealing explanatory factor because alternative approaches have failed to convey a plausible account of the sharp increase of European unemployment. Exogenous factors like the oil shock in the early and late 1970s, a productivity slowdown in the 1980s and 1990s as well as increased international competition from newly developing countries may all have had a negative impact on European labour markets but most of these factors also affected the United States where the increase of unemployment has by no means reached the intensity observed in Europe. Thus, consistent with the Eurosclerosis hypothesis and unlike the United States, it seems that the European labour market doesn’t have the mechanisms and the flexibility to absorb shocks as the above-mentioned and quickly respond to new circumstances. In contrast, it is observed that labour market responds more slowly than the shocks to labour demand/supply warrant. Many economists indicate adjustment costs to be accountable for this, providing to us the motive for this work.

An additional motive was the increasing concern of labour literature in the last years about the modeling of employment decisions at micro level. Firms face costs if they choose to adjust their staffing levels and, in the context of labour demand, adjustment costs are introduced to account for the fact that, in response to a certain shock, a firm will in general be unable to immediately set employment to the level that it perceives as optimal. During recessions firms hoard labour and during expansions they may operate to some extent understaffed in order to avoid the cost of adapting employment to the level they would attain in the absence of adjustment costs.

A large empirical and theoretical literature has investigated the dynamics of employment at the firm or plant level and reached the conclusion that these are usually explained by positing certain structures of adjustment costs. For analytical and econometric convenience, the literature initially adopted quadratic function for the adjustment costs. This standard assumption of the early dynamic labour demand literature implies that employment will adjust frequently in small amounts but not in large amounts. An additional important restriction is that the quadratic adjustment cost assumption imposes symmetry on the costs of positive and negative adjustments. That is, hirings and firings of employees are assumed to be equally costly when of the same magnitude.

The above features are strongly at odds with data on employment, as pointed out by micro-level empirical research for adjustments to the employment level. Hamermesh (1989) for instance, using monthly data on seven manufacturing plants provides a revealing discussion of lumpy labour adjustment environment and proposes the introduction of a fixed component in the adjustment cost function. Davis and Haltiwanger (1992) document large employment changes at the plant level. Caballero, Engel and Haltiwanger (1997) report evidence of inactivity in plant-level adjustment: a large number of plants in the US choose not to adjust their employment, even when shortages are large. Similarly, Varejao and Portugal (2003)

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1 They show that in the Longitudinal Research Database 25 percent of the employment growth rates lie in the interval [-0.05, 0.05].
report that 75 percent of their large sample of Portuguese plants does not adjust employment from one quarter to the next.

Overall, there seems little doubt that an explanation of firm level employment dynamics requires a model of adjustment that is richer than the quadratic adjustment cost structure and includes forms of non-differentiability and/or non-convexity. Convex cost alone can not explain adjustment of employment and one also needs fixed or linear costs.

1.2 This work

This paper studies dynamic labour demand at micro level. Understanding firm-level observations on the labour input requires a model with rich specifications of adjustment costs. Specifications which ignore labour adjustment costs or assume quadratic adjustment costs only, are unable to match the firm-level infrequent dynamic pattern of employment activity. The importance of non convexities in adjustment costs has been pointed out by many researchers, as we saw above. The aim of this paper is to go beyond these studies by estimating these adjustment costs with a fully specified structural model at micro level.\(^2\) In contrast to this paper, a lot of the earlier empirical work on employment dynamics at the firm level using panel data does not provide direct estimates of adjustment costs. Rather in the early work the emphasis is on the dynamics of employment where in the estimates of the dynamic employment regressions it is impossible to retrieve the structural adjustment cost parameters.\(^3\)

Our approach specifies a dynamic structural model of employment at the firm level in order to get a better understanding of microeconomic employment changes. Its target is to look into the dynamic nature of labour adjustment costs Greek firms face when they decide to hire/fire employees. In addition to this, we monitor if the Greek micro data supports the presence of both convex and non-convex components of adjustment costs and more specifically we find the structural estimates of these components that are consistent with the micro-evidence for the Greek economy. Our work, as far as we know, constitutes the first attempt of studying the employment behavior of Greek economy at the micro level. As a result, we hope that this work not only contributes to the better understanding of the complex dynamics of employment, but it also constitutes an essential tool for the evaluation of different policies regarding Greek economy.

Based on the evidence of our dataset and following Cooper and Haltiwanger (2006) we introduce a dynamic discrete choice model with a general specification of adjustment costs including both convex and non-convex components. Furthermore, the adjustment cost literature has convincingly argued that the traditional convex cost is not sufficient to explain employment changes. The firm has to hire/fire employees in complete units and therefore the model is not differentiable in employment and has to be solved numerically. This is done by implementing the numerical method, Value Function Iteration method, which is summarized in subsequent section. In order to estimate the structural parameters of the model, we use a simulated moments procedure. The method of simulated moments essentially estimates the structural parameters of the model by matching the moments of the data with the moments of the model. This paper therefore goes beyond most of the relevant literature in estimating a fully structural model of employment adjustment.

\(^2\) Two other papers that estimate a fully structural model on US data are Cooper, Haltiwanger and Willis (2004) and Cooper and Willis (2004). Their analysis however relies on aggregate observations of employment and includes plant-level hours growth. This paper remains in the spirit of the dynamic labour adjustment literature and focuses on the adjustment in number of employees and not in hours, maintaining the common assumption that labour input into the production can be proxied by the number of employees. This is because hours data at the firm level are not available for Greece.

\(^3\) See for example Arrellano and Bond (1991), Nickel and Wadhwani (1991) and Bresson et al. (1992).
The rest of the paper is structured as follows. In section 2 the data is described. In section 3 the dynamic structural model of employment is developed and in section 4 we describe the estimation: the methodology (section 4.1), the estimation method we implement (section 4.2) and the estimation results (sections 4.3 and 4.4). Section 5 gathers the main implications of the empirical analysis and concludes.

2. Data Set

The main data source in this paper is the ICAP firm-level database. The ICAP is the largest company providing economic data and consultative services in Greece and is a member of the international network INFOALLIANCE and participant of the European economic and business information network EUROGATE. The company is also a member of Federation of Business Information Services (FEBIS), European Association of Directory and Database Publishers (EADP), European Federation of Management Consulting Association and a member of the international research organization GALLUP INTERNATIONAL.

The ICAP database contains balance sheet statements of Greek firms. Our data are a balanced panel of 2838 Greek manufacturing firms over the period 1998-2004 containing 19866 observations. These are the data we get after filtering all the manufacturing firms that are registered in the ICAP databank, depending on the availability of the labour data. We delete firms with missing data points between 1998 and 2004. Since net profits are an essential variable to our analysis, we only keep manufacturing firms that have profits information. Firms are also dropped if they have a large outlier observation in the seven year period. The outliers are defined as a growth rate of employment more than 200% in a given year. This leads to our final dataset of 2790 firms on 19530 observations.

The dataset is balanced and each firm has exactly 7 observations. The 2790 manufacturing firms comprise a considerable portion of the active Greek manufacturing firms: in 2004 they represented about 45 percent of the total population of Greek manufacturing and 54.3 percent of employment. Their total net profits were 2 billion euro, while the total manufacturing industry in Greece had net profits of 2.1 billion euro.

A limitation of this work -which has to do with the data-, just like in most dynamic labour adjustment studies, is the absence of data regarding hours worked. However, aggregate yearly manufacturing data suggest that adjustment, over a year, takes place in terms of number of people working rather than hours.

Summary Statistics

For the purpose of analysis the firms are split into four size groups according to the average number of employees over the period 1998-2004 (Table 1).

<table>
<thead>
<tr>
<th>label</th>
<th># employees</th>
<th># firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>micro</td>
<td>1 to 9</td>
<td>317</td>
</tr>
<tr>
<td>small</td>
<td>10 to 49</td>
<td>1677</td>
</tr>
<tr>
<td>medium</td>
<td>50 to 249</td>
<td>655</td>
</tr>
<tr>
<td>large</td>
<td>250 and more</td>
<td>141</td>
</tr>
</tbody>
</table>
It should be noted that all statistics in this paper are calculated as across firms’ averages: first statistics are calculated for each individual firm over the period 1998-2004 after which the average across firms of these statistics is calculated.

Table 2 shows summary statistics of the yearly employment changes (number of workers in logs) for all firms and for each size group partially.

Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>group</th>
<th>mean</th>
<th>median</th>
<th>std dev</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>1</td>
<td>1</td>
<td>10.33</td>
<td>-1729</td>
<td>1007</td>
</tr>
<tr>
<td>micro</td>
<td>0</td>
<td>0</td>
<td>1.65</td>
<td>-45</td>
<td>25</td>
</tr>
<tr>
<td>small</td>
<td>0</td>
<td>0</td>
<td>4.09</td>
<td>-100</td>
<td>50</td>
</tr>
<tr>
<td>medium</td>
<td>2</td>
<td>2</td>
<td>15.34</td>
<td>-205</td>
<td>183</td>
</tr>
<tr>
<td>large</td>
<td>5</td>
<td>4</td>
<td>80.7</td>
<td>-1729</td>
<td>1007</td>
</tr>
</tbody>
</table>

$H_t = L_{t+1} - L_t

<table>
<thead>
<tr>
<th>group</th>
<th>mean</th>
<th>median</th>
<th>std dev</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>70</td>
<td>70</td>
<td>11.54</td>
<td>0</td>
<td>4089</td>
</tr>
<tr>
<td>micro</td>
<td>6</td>
<td>6</td>
<td>1.75</td>
<td>0</td>
<td>45</td>
</tr>
<tr>
<td>small</td>
<td>25</td>
<td>25</td>
<td>4.57</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>medium</td>
<td>102</td>
<td>102</td>
<td>18.58</td>
<td>0</td>
<td>430</td>
</tr>
<tr>
<td>large</td>
<td>604</td>
<td>605</td>
<td>83.75</td>
<td>0</td>
<td>4089</td>
</tr>
</tbody>
</table>

Table 3: Features of the employment growth distribution

<table>
<thead>
<tr>
<th>Fraction of observations (%)</th>
<th>all</th>
<th>micro</th>
<th>small</th>
<th>medium</th>
<th>large</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_\alpha &gt; 10$</td>
<td>8.7</td>
<td>0.3</td>
<td>3.6</td>
<td>21.2</td>
<td>29.3</td>
</tr>
<tr>
<td>$H_\alpha == 0$</td>
<td>57.1</td>
<td>70.0</td>
<td>60.6</td>
<td>46.8</td>
<td>34.5</td>
</tr>
<tr>
<td>$H_\alpha &lt; -10$</td>
<td>6.7</td>
<td>0.8</td>
<td>3.9</td>
<td>12.2</td>
<td>28.0</td>
</tr>
</tbody>
</table>

autocor:

| $(H_\alpha, H_{\alpha-1})^1$ | -0.19672 | -0.16877 | -0.19781 | -0.19714 | -0.232 |
| $(H_\alpha, H_{\alpha-2})^1$ | -0.13711 | -0.12176 | -0.16417 | -0.09594 | -0.08552 |
| $(H_\alpha, H_{\alpha-3})^1$ | 0.00274  | 0.03247  | 0.00403  | 0.00210  | -0.05932 |

1. Labour is in logs: $H_\alpha = \log(L_t) - \log(L_{t-1})$
Figure 1: Employment growth distributions

all firms sample

micro firms sample

small firms sample

medium firms sample

large firms sample

labour changes ($\Delta L$)

% of observations

0% 10% 20% 30% 40% 50% 60% 70%

-25 -20 -15 -10 -5 0 5 10 15 20 25
Figure 1 depicts the distribution of the employment changes for the period 1999-2004 for each size-group and Table 3 shows some features of these distributions.

All statistics are calculated by pooling data for 2790 manufacturing firms and for the period 1998-2004. In that period the median firm had 70 employees and an employment change at 1. With regard to size groups the correspondingly moduli are also depicted in Table 2. The average number of employees is 70 (6 for the micro and 25 for the small groups, 102 for the medium group and 604 for the large group) and the average employment change is by 1 employee (0 for the micro and small groups, 2 for the medium group and 5 for large firms). The average standard deviation across firms of employment change is 10.33.

When looking Figure 1 and Table 3, the distribution of employment growth indicates some very interesting stylized facts that have also been emphasized by other researchers in relevant works. The remarkable feature of the employment growth distribution in Greek manufacturing is the infrequent nature of labour adjustment: there are many periods in which employment stays fixed from one year to another. The frequency of non-adjustment is 57.1 percent for the set of firms in the dataset. That is, an average firm keeps employment fixed from year to year in 57.1 percent of the total period of seven years. In respect of size groups, the frequency of non-adjustment is 70.0 percent for the micro firms and 60.6 percent for the small firms and gradually declines to larger size groups: 46.8 percent for the medium firms, 34.5 percent for the large firms.

So the first stylized fact is that the frequency of no adjustment is high for all firms, especially high for small firms but gradually declines for larger firms.

An employment positive (negative) spike is defined as more (less) than 10 people hiring (firing). The fraction of observations in this region is only 8.7 (6.7) percent for the set of firms, 0.3 (0.8) percent for micro firms, 3.6 (3.9) percent for small group, 21.2 (12.2) percent for the medium sized group and 29.3 (28.0) percent for large firms. Therefore, the second stylized fact is that there are sporadic periods of large employment changes.

Table 3 also depicts the autocorrelation of employment growth at lags one, two and three. In the ensemble and in all size groups, the first two autocorrelations, which are the appreciable ones, take negative sign indicating the third stylized fact: high employment growth episodes are followed by low growth episodes.

Recapitulating, the empirical evidence reported in this section stresses three important stylized facts: (a) there are periods in which firms decide not to change their labour input and stay inactive, (b) there are periods of large employment changes (lumpy nature of labour adjustment) and (c) the commonality is employment spikes to be followed by smooth and low employment growth periods.

The above three stylized facts clearly back up the adoption of a labour model which accounts for infrequent activity and lumpiness. We develop a relevant model below.

3. Theoretical Model

The model abuts against Cooper and Haltiwanger (2006) with the difference that the quasi-fixed factor of production here is labour. We assume a large and fixed number of firms. Let

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\(L_i\) represent the stock of current workers employed by firm \(i\) in the beginning of period \(t\). Before making any adjustment decision, the firm observes the current period profitability shock. Given this state variable, the firm makes an employment decision depending on the nature of labour adjustment costs.

The firm’s dynamic programming problem is given by:

\[
V(A_{it}, L_{it}) = \max_{[H_{it}]} \Pi(A_{it}, L_{it}) - C(H_{it}, L_{it}) + \beta E_{A_{i+1}} V(A_{i+1}, L_{i+1})
\]

subject to the following constraint:

\[
H_{it} = L_{i+1} - L_{it}
\]

where the profit function is parameterized in the following way:

\[
\Pi(A_{it}, L_{it}) = A_{it} L_{it}^\theta
\]

where \(0 < \theta < 1\) is the curvature of the profit function. Note the timing assumption of the model: workers hired in a given period become productive in the next period. \(A_{it}\) is the current period profitability shock that contains both an idiosyncratic component, as well as an aggregate one. It is assumed that labour is the only quasi-fixed factor of production and all variable factors have already been maximized out of the problem. The costs of adjustment are given by the function \(C(H_{it}, L_{it})\). \(H_{it}\) is the net, not gross, hires/fires firm’s manager chooses.\(^7\) The function \(C(H_{it}, L_{it})\) has components of both convex and non-convex costs of adjustment. The discount factor, \(\beta\), is fixed and equals \((1 + r)^{-1}\), where \(r\) is the risk-free market interest rate.

3.1. Adjustment Cost Structures

The shape of the adjustment cost function is crucial for the dynamic behavior of the firm. The forms that have been suggested in the literature are fixed, linear, concave and concave-convex functions of adjustment costs.\(^8\) In its most general form, we assume that the cost of adjustment function is given by (bellow we discuss in more details the partial components of the function):

\[
C(H_{it}, L_{it}) = F + \frac{\xi}{2} \left( \frac{L_{i+1} - L_{it}}{L_{it}} \right)^2 L_{it} + (1 - \lambda) \Pi(A_{it}, L_{it})
\]

\(^7\) Due to data limitations we are unable to detect gross hires and fires. The quit rate plays no role in the firm’s optimization problem.

\(^8\) These forms have been tested separately in several papers. For an extensive review see Hamermesh and Pfann (1996).
Adjustment cost functions are not empirically observable. However, simulation results provide a better clue as to how different functional forms for adjustment costs imply different adjustment patterns. As suggested by e.g. Cooper and Haltiwanger (2006) and Abel and Eberly (1994, 2002), attention is given to the estimation of a unified model that incorporates different types of adjustment costs. Costs associated with search and recruiting, reorganization of production activities, training, firing, etc. are some of the costs covered by the adjustment cost function.

**Convex Labour Adjustment Costs**

Traditionally, a symmetric convex adjustment cost function is assumed, usually quadratic, like:

\[ C(H_{it}, L_{it}) = \frac{\xi}{2} \left( \frac{H_{it}}{L_{it}} \right)^2 L_{it} \]  \hspace{1cm} (5)

This is the standard specification in the literature. The costs of adjustment are assumed to be a quadratic function of the percent change in the stock of employed workers multiplied by the initial stock of employees. The parameter \( \xi \) affects the magnitude of total and marginal adjustment costs. The higher the \( \xi \) is, the higher the marginal cost of employment adjustment is and thus the lower the responsiveness of employment to variations in the underlying profitability of labour is.

**Non Convex Labour Adjustment Costs**

Convex labour adjustment costs cannot match the findings of recent empirical studies for lumpiness of employment adjustment. Firms tend to concentrate their employment adjustment into short periods of time. Consequently, firms exhibit frequent periods of no adjustment (inaction). Therefore, it has been suggested to add fixed costs components to the adjustment cost function. Here we allow the case of a component of costs being fixed when firing/hiring is undertaken regardless of the hiring/firing’s magnitude. The structural parameter \( F \) determines the magnitude of fixed cost of hiring or firing workers. The firm incurs an additive cost of \( F \) in each period there is a net hire or fire. Activities like the posting of an advertisement of vacancies, the review of material provided by candidates, and the interviews, clearly support the existence of fixed costs in hiring new employees. We should emphasize that when there are no fixed costs associated with labour adjustment, the value function is continuous and concave. The introduction of fixed adjustment costs breaks the concavity.

The distinctive characteristic of the pattern of employment adjustment implied by non-convex adjustment costs is the infrequent moments of sharp employment adjustment (spikes) in the firm level employment record.

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9 Nickell (1986), Hamermesh (1993) and Hamermesh and Pfann (1996) provide a lengthy discussion of various interpretations and motivations for adjustment costs.

10 Specifications in which quadratic adjustment costs are in terms of employment changes alone and not of percent differences can also be found in the literature (Hamermesh [1989]).

Disruption Cost

Caballero and Engel (1999), Cooper, Haltiwanger and Willis (2004) and Cooper and Haltiwanger (2006) assume and find support for disruption costs: labour adjustment disrupts the production process so that the firm loses a fraction of revenue each time there is a net change in the number of workers. This is modeled by introducing the term \((1 - \lambda)\Pi(K_n, L_n)\) in the adjustment cost function. \((1 - \lambda)\) is the fraction of revenue lost during employment adjustment. An important thing is that while fixed cost does not interact with the state of profitability, the disruption cost implies that adjustment is more costly during periods of high profitability.

3.2. Value Maximization

The firm manager’s dynamic program can be written as follows:

\[
V(A_n, L_n) = \max \{V^A(A_n, L_n), V^{NA}(A_n, L_n)\} \quad (6)
\]

The manager needs to choose optimally between adjusting employment, with value \(V^A(.)\) and not adjusting employment at all, with value \(V^{NA}(.)\). These two alternative options have a value, given by:

\[
V^A(A_n, L_n) = \max_{H_n} \Pi(A_n, L_n) - \frac{\varepsilon}{2} \left[ \frac{H_n}{L_n} \right]^2 L_n - F - (1 - \lambda)\Pi(A_n, L_n) + \beta E_{A_{n+1}/A_n} V(A_{n+1}, L_{n+1})
\]

\[
\text{if } H_n \neq 0 \quad (6a)
\]

subject to the constraint \(H_n = L_{n+1} - L_n\)

\[
V^{NA}(A_n, L_n) = \Pi(A_n, L_n) + \beta E_{A_{n+1}/A_n} V(A_{n+1}, L_n) \quad \text{if } H_n = 0 \quad (6b)
\]

In this framework, there will be periods of inaction when fundamentals are not favorable and periods of bursts of employment changes when fundamentals are high or low enough. The firm hires/fires workers when its labour stock is less/more than its optimal level otherwise prefers to avoid adjustment costs and remains inactive. Equation (6a) gives the value of adjusting workers as the profits minus total costs under the optimal decision, plus the discounted future value, given this period’s decision and optimal behavior in subsequent periods. Equation (6b) gives the value of no adjustment, which of course does not involve any costs or maximization.

Since inaction is an option due to the presence of non strictly-convex adjustment costs, there is the possibility of corner solutions in the demand for labour. In this case, the standard marginal conditions for optimality given by the Euler equation fail to hold. In the model presented above, we explicitly take into account the existence of corner solutions by considering a discrete-time-discrete-choice dynamic structural model. Previous studies which

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12 Cooper and Haltiwanger (1993) discuss these types of adjustment costs.
have adopted continuous time-state-space framework have not provided direct estimators of the structural parameters, due to the difficulty of obtaining closed-form solutions.\(^{13}\)

The discontinuity in the employment change process makes analytical solution of the model infeasible. The model is solved using a numerical method known as the Value Function Iteration method. This method can be summarized as follows. Let \( V \) be the value function. The value function iteration starts with some initial value \( V_0 \) and then evaluates \( V_{j+1} = T(V_j) \) for \( j = 0,1,2,... \) (where \( T \) is a mapping operator). The desired value function is obtained when the difference between \( V_{j+1} \) and \( V_j \) is less than some predetermined threshold value.\(^{14}\)

The set of the structural parameters is \( \{\beta, \theta, \xi, F, \lambda\} \). These together with the transition matrix for the profitability shocks determine the behavior of the model.

4. Estimation of the Model

4.1. Methodology

Our goal is to estimate the adjustment costs for labour. The methodology is described in the subsequent sections.

4.1.1. Estimation of the profit function

The profit function is given by

\[
\Pi(A_t, L_t) = A_t L_t^\theta
\]

where \( A_t \) is the profitability shock, \( \theta \) is labour share and \( L_t \) is the firm level labour stock.

In the model, it is assumed that labour is the only quasi-fixed factor of production and all the variable factors have already been maximized out of the problem. We estimate \( \theta \) by regressing the natural log of real net profit (net of cost of production) on the natural log of labour input \( L_t \) and the natural log of real capital using firm level Greek panel data. Although \( \theta \) is assumed to be the same for each firm at each period, we remove fixed effects in order to take into account the structural differences across firms (in order to fix the structural heterogeneity problem).\(^{15}\) From our data \( \theta \) is estimated at 0.54, with a standard error of 0.038.

4.1.2. Calculation of the profit shocks

Following Cooper and Haltiwanger (2006), the profitability shock consists of two exogenous components: an aggregate shock and an idiosyncratic shock (\( a_{it} \)). We calculate the

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\(^{13}\) See for example Bentolila and Bertola (1990).

\(^{14}\) See Rust (1987a, b) for details.

\(^{15}\) We remove fixed effects by presenting profits, labour input and capital as deviated from the firm-level mean.
idiosyncratic component \((a_t)\), through regressing the natural log of net profit (net of cost of production) on the natural log of labour input \(L\) and the natural log of capital including time dummies, after removing the fixed effects, and taking the residuals.\(^{16}\) Table 4 shows some features of the idiosyncratic profitability shocks.

**Table 4: Features of the idiosyncratic profitability shocks, \(a_t\)**

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.000</td>
</tr>
<tr>
<td>Median</td>
<td>0.007</td>
</tr>
<tr>
<td>Minimum</td>
<td>-5.64</td>
</tr>
<tr>
<td>Maximum</td>
<td>3.88</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>0.7431</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.16</td>
</tr>
</tbody>
</table>

**4.1.3. Simulations**

- We fix the discount factor \(\beta\) at the empirically reasonable value 0.97.\(^{17}\) We have also estimated the model with different values of \(\beta\) (0.95 and 0.99) obtaining similar results.
- The curvature of the profit function, \(\theta\), is estimated as 0.54.
- We assume that the idiosyncratic profitability shocks follow an AR(1) process:\(^{18}\)

\[
a_{t+1} = \rho a_t + \varepsilon_{t+1} \quad \text{where} \quad \varepsilon_{t+1} \sim iid \ N(0, \sigma^2) \quad (7)
\]

- We approximate this process by a discrete Markov process using the method outlined in Tauchen (1986). A time invariant Markov chain is defined by \((Z, T)\), where \(Z \in \mathbb{R}^n\) is a vector describing the states possible of the Markov process, and \(T\) is an \(n \times n\) dimensional transition matrix with elements \((i, j)\) that express the probability of transition from state \(Z_i\) to state \(Z_j\). Thus, the rows of \(T\) sum to unity.\(^{19}\) The method proposed by Tauchen (1986) is used to create a discrete state space representation of the stochastic AR(1) process for the firm specific shocks. The idiosyncratic shocks take 11 different values. The serial correlation of the idiosyncratic shocks is 0.16. The standard deviation is 0.7. Table 5 presents the idiosyncratic shocks and the transition matrix of these shocks. The transition matrix for the idiosyncratic shocks is computed from the empirical transitions observed at the firm-level and reproduces statistics from the idiosyncratic profitability shock series.

---

\(^{16}\) Since we remove fixed effects, include time dummies, and the variables are taken in log form, the residual shocks are the firm specific idiosyncratic shocks in log form (time dummies capture the aggregate component of the profitability shocks).

\(^{17}\) \(r\) is set approximately at 3 percent which is the average real interest rate on government bonds in Greece.

\(^{18}\) It is very common to the firm level literature to assume first order process for the underlying shocks. See e.g. Olley and Pakes (1996) and Levinsohn and Petrin (2000). Our specification of the relatively simple AR(1) process for the idiosyncratic shocks is motivated by the need to keep the state space relatively parsimonious and thus more informative for the downstream numerical analysis and estimation.

\(^{19}\) See Ljungqvist and Sargent (2000, Chapter 1), Stokey and Lucas (1989, Chapters 8, 11 and 12) and Adda and Cooper (2003).
We solve the dynamic programming problem via the Value Function Iteration method and we create simulated data. We estimate the remaining structural parameters using the method of simulated moments.

4.2. Estimation Method: Method of Simulated Moments

The vector of remaining structural parameters to be estimated is \( \Theta = (\xi, F, \lambda) \). The approach is to estimate these parameters by matching the implications of the structural model with key features of the data. The methodology that is used for this purpose is the structural empirical approach called method of simulated moments. This method works as follows.

With an arbitrary set of parameter values and by using the Value Function Iteration method we solve the firm’s dynamic programming problem. After the model is solved for given \( \Theta \) values, a 500 firms and 100 periods simulated panel data are obtained using the created policy functions. This simulated data set is used to calculate the model analogues of the moments we obtained using actual data. The three key moments of the firm level adjustment dynamics that we seek to match are the autocorrelations of employment growth at lags 1, 2 and 3. Denoting as \( \Psi^d \) the vector of moments from the actual data and as \( \Psi^s(\Theta) \) the vector of moments from data simulated given \( \Theta \), the simulated moments routine looks for the structural parameter estimates that minimize the weighted distance between the two vectors of moments. More formally, the statistic we try to minimize with respect to \( \Theta \) in order to find the structural parameter values is the following quadratic function:

\[
J(\Theta) = (\Psi^d - \Psi^s(\Theta))^TW(\Psi^d - \Psi^s(\Theta))
\]

where \( W \) is a weighting matrix. The vector of true moments is \( \Psi^d = \begin{bmatrix} \text{corr}(H_u, H_{it-1}), \text{corr}(H_u, H_{it-2}), \text{corr}(H_u, H_{it-3}) \end{bmatrix} = [-0.20, -0.14, 0.003] \). Given the

---

\[20\] See section 3.2.

\[21\] As pointed by Gourieroux and Monfort (1996), minimizing the distance between the simulated data moments and the actual data moments will emerge consistent estimates of the structural parameters.

\[22\] We implement the 5x5 identity matrix. Cooper, Haltiwanger and Willis (2004) use a weighting matrix based on the variances of the moments estimated.
discontinuities in the model and the discretization of the state space, as it is the case in related studies, we use the method of simulated annealing in order to minimize \( J(\Theta) \) with respect to \( \Theta \). As Bayraktar, Sakellaris and Vermeulen (2005) notice, simulated annealing is the ideal algorithm for dealing with complex functions, first because it explores the function’s entire surface and can escape from local optima by moving uphill and downhill and second, because the assumptions required with respect to functional forms are quite relaxed.

### 4.3. Estimation Results

Using the method of simulated moments, the structural parameters of the model are estimated. Table 6 gives the estimated values of five models: quadratic adjustment costs (QAC), fixed costs (FC), disruption cost (DC), all (ALL) QAC, FC and DC together. The fifth model allows for the presence of both quadratic and disruption costs (QAC+DC). The separate estimation of the first three adjustment cost forms makes clear the significant role of fixed and disruption costs at the firm level relative to quadratic adjustment cost model. The last model was the combination of the first three special cases that resulted in a superior fit of the model to the data, just like in Cooper, Haltiwanger and Willis (2004). Table 7 focuses on the comparison of the simulated data results with the actual data results and gives the four moments of actual and simulated data.

Table 6 illustrates the prominent role of disruption costs in matching observations at the firm level, as measured by the relatively low value of \( J(\Theta) \). The disruption case model mimics better the negative first and second order autocorrelation of the employment growth and generates variability in employment growth relatively close to the actual data one, than the other two of the first three models.

### Table 6: Estimated Structural Parameters and function value

<table>
<thead>
<tr>
<th>Model</th>
<th>( \xi )</th>
<th>( F )</th>
<th>( \lambda )</th>
<th>( J(\Theta) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>QAC</td>
<td>0.667</td>
<td></td>
<td></td>
<td>2.7324</td>
</tr>
<tr>
<td></td>
<td>(0.1036)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FC</td>
<td>0.9955</td>
<td></td>
<td></td>
<td>0.0555</td>
</tr>
<tr>
<td></td>
<td>(0.0454)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC</td>
<td></td>
<td>0.9464</td>
<td></td>
<td>0.0434</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0053)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALL</td>
<td>0.6584</td>
<td>0.0006</td>
<td>0.9841</td>
<td>0.0359</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>QAC+DC</td>
<td>0.5630</td>
<td>0.9842</td>
<td></td>
<td>0.0359</td>
</tr>
<tr>
<td></td>
<td>(0.0215)</td>
<td>(0.0007)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: standard errors are reported in parentheses

The fixed adjustment cost model also mimics more efficiently the negative first and second order autocorrelation of the employment growth compared to the quadratic model.

The quadratic adjustment cost model has the worst performance: the value of \( J(\Theta) \) is the highest and the model is unable to match the first and second order autocorrelation of the employment growth.
The model allowing for all cases of costs to be together comes closest to the actual data results. It is important here to note that in this case, the parameter for the fixed cost is extremely small (0.0006) and does not improve the fit of the simulated moments to the actual data: the value of $J(\Theta)$ is the same even if we exclude the fixed adjustment cost parameter from the model.

Table 7: Moments of actual data versus moments of simulated data

<table>
<thead>
<tr>
<th>Model</th>
<th>$\text{cor}(H_{n},H_{n-1})$</th>
<th>$\text{cor}(H_{n},H_{n-2})$</th>
<th>$\text{cor}(H_{n},H_{n-3})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Data</td>
<td>-0.20</td>
<td>-0.14</td>
<td>0.003</td>
</tr>
<tr>
<td>QAC</td>
<td>-0.9701</td>
<td>0.9600</td>
<td>-0.9499</td>
</tr>
<tr>
<td>FC</td>
<td>-0.1674</td>
<td>-0.1781</td>
<td>-0.1769</td>
</tr>
<tr>
<td>DC</td>
<td>-0.1069</td>
<td>-0.1150</td>
<td>-0.1144</td>
</tr>
<tr>
<td>ALL</td>
<td>-0.2258</td>
<td>-0.2344</td>
<td>-0.0714</td>
</tr>
<tr>
<td>QAC+DC</td>
<td>-0.2258</td>
<td>-0.2344</td>
<td>-0.0714</td>
</tr>
</tbody>
</table>

Note: $H_{n} = \log(L_{n})-\log(L_{n-1})$ is the growth rate of employment.

Synopsizing, our findings indicate that the quadratic adjustment costs alone fail to match the firm-level moments. We find that the principle cost of labour adjustment is the disruption of the production process. This cost is needed to match firm-level observations on the autocorrelation structure of employment growth. Furthermore, a model with both quadratic and disruption costs does substantially better than a quadratic model because yields micro predictions that are very close with the micro evidence.

“The best fit” model (QAC+DC) has a convex cost parameter estimate at 0.5630 implying a convex cost of 56.3% per worker hired/fired (squared), which is in general comparable to the existing literature but higher than the value structurally estimated by Cooper, Haltiwanger and Willis (2004) for manufacturing plant-level data set for the US (0.00003). The estimate of $\lambda$ (0.98) implies that a firm loses 2% of its revenues during an adjustment period. While this loss may seem small it is not, first because is hinting a relatively high inaction rate and second because is higher than the estimate found by Cooper and Willis (2004) for the US (1%).

4.4. Firm-Size Estimation Results

The above estimates of adjustment costs are based on the assumption that the parameters are common to all firms in our panel. In this subsection, we report some estimates using micro (1 to 9 employees), small (10 to 49 employees), medium (50 to 249 employees) and large (250 and more employees) firms. The motivation for undertaking this exercise is to see whether our results are sensitive to the size of the firm.

Tables 8 and 9 summarize our findings. Here we only estimate an adjustment cost model that includes both the quadratic and disruption cost specifications, as in the overall manufacturing estimates this was the model with the best performance.

Tables 8 and 9 indicate again strict concavity of the profit function as well as small serial correlation of the shocks. In terms of the adjustment costs, we see clearly again that disruption costs are substantially present. Interestingly, these disruption costs are much more prominent for large firms and go down for smaller firms. It is obvious that larger firms have to deal with smaller convex adjustment costs but higher disruption when they decide to change their
employment. We estimate the convex adjustment cost parameter $\xi$ to be only 0.1042 and the disruption cost parameter $\lambda$ to be 0.9761 for large firms. Higher convex adjustment costs and smaller disruption are estimated for small-medium sized firms: $\xi$ is found to be around 0.3 and $\lambda$ is estimated to be 0.98. Finally, micro firms encounter the highest convex adjustment costs and the lowest disruption when they change their labour: $\xi$ is estimated to be 0.6759 and the disruption cost parameter ($\lambda$) reaches 0.9937.

<table>
<thead>
<tr>
<th>Firm size</th>
<th>Structural Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\theta$</td>
</tr>
<tr>
<td>micro</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
</tr>
<tr>
<td>small</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
</tr>
<tr>
<td>medium</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
</tr>
<tr>
<td>large</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
</tr>
</tbody>
</table>

Note: standard errors are reported in parentheses

<table>
<thead>
<tr>
<th>Firm size</th>
<th>Moments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\text{cor}(H_{it}, H_{it-1})$</td>
</tr>
<tr>
<td>micro: actual</td>
<td>-0.168</td>
</tr>
<tr>
<td>simulated</td>
<td>-0.2286</td>
</tr>
<tr>
<td>small: actual</td>
<td>-0.198</td>
</tr>
<tr>
<td>simulated</td>
<td>-0.2304</td>
</tr>
<tr>
<td>medium: actual</td>
<td>-0.197</td>
</tr>
<tr>
<td>simulated</td>
<td>-0.2286</td>
</tr>
<tr>
<td>large: actual</td>
<td>-0.232</td>
</tr>
<tr>
<td>simulated</td>
<td>-0.2267</td>
</tr>
</tbody>
</table>

Note: $H_{it} = \log(L_{it}) - \log(L_{it-1})$ is the growth rate of employment.

5. Conclusions

This paper studies labour adjustment costs by estimating a dynamic model of employment for Greek manufacturing firms. A balanced panel dataset of 2790 firms on 19530 observations for the period 1998-2004 has pointed strong evidence of inaction and lumpy employment. On account of these empirical observations and following Cooper and Haltiwanger (2006) we adopt and compare models with alternative labour adjustment costs and we show that the models with only one type of adjustment cost are not successful in matching the dynamic nature of employment. 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 only does substantially better than a quadratic model but does not match the firm-level data as well as a model which combines quadratic adjustment costs and disruption costs. Disruption of the production process is evidently found to be the principle cost of labour adjustment. Disruption
costs are needed to match firm-level observations on the autocorrelation structure of employment growth.

We estimate the structural parameters of the model, using the method of simulated moments (described in section 4.2). The results indicate the importance of both convex and non-convex adjustment costs and imply that traditional representative agent models with just convex costs of adjustment are incapable of capturing the dynamics of employment growth. Labour adjustment costs are more complex than we once thought. Furthermore, with regard to the size of the adjustment costs, our findings confirm the evidence of high costs associated with adjusting employment in the Greek economy.

One of the gains to structural estimation presented in the present paper is to use the estimated parameters for policy analysis. The knowledge of structure of labour adjustment costs is crucial for predicting the possibly long and complex path of responses of labour demand to shocks, therefore should be a basic input into debates over the long-run effects of policies that concern employment. Our next work will be the evaluation of the estimated model in terms of its predictions of the (dis)aggregate effects of different labour policies. Public policy plays an important role in the firm’s employment decisions and we will attempt to model this and to see how adjustment costs influence the effectiveness of fiscal policy.

References


Gourieroux C; and A. Monfort, (1996), Simulation Based Econometric Methods, Oxford University Press.


