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ABSTRACT

Spatial and Temporal Aggregation in the Estimation of Labor Demand Functions*

The consequences of aggregation, temporal or spatial, for the estimation of demand models are theoretically well-known, but have not been documented empirically with appropriate data before. In this paper we conduct a simple, but instructive, exercise to fill in this gap, using a large quarterly dataset at the establishment-level that is increasingly aggregated up to the 2-digit SIC industry and the yearly frequency. We only obtain sensible results with the quadratic adjustment cost model at the most aggregated levels. Indeed, the results for quadratic adjustment costs confirm that aggregation along both dimensions works to produce more reasonable estimates of the parameters of interest. The fixed adjustment cost model performs remarkably well with quarterly, but also with yearly, data. We argue that is may be one more consequence of the unusually high labor adjustment costs in the Portuguese labor market.

JEL Classification: J21, J23

Keywords: labor demand, adjustment costs, aggregation

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1 Introduction

Early studies of labor demand typically impose an autoregressive structure assuming that total employment adjusts smoothly to its long-run equilibrium. This kind of model, which proved well-fitted to aggregate (industry or national-level) data, was subsequently rationalized at the micro-level with a profit maximizing firm facing convex symmetric costs of adjustment of the labor input (Holt et al., 1960). As a consequence, quadratic adjustment costs became standard in the dynamic theory of labor demand.

Aggregation of linear micro-relations relies on the validity of either a micro-homogeneity condition (the equality of the parameters in the micro-relations corresponding to each individual in the aggregate) or a compositional stability condition (the constancy over time of the distribution of regressors across the population that makes up the aggregate). If neither of these conditions holds, a specification error (due to the omission of all the micro-variables in the macro-equation) emerges. This error is called aggregation bias. [1]

Let us consider the implications towards the study of labor demand. If only aggregate data are available, in general it is not possible to incorporate individual heterogeneity and distributional issues in the (macro) model. If the true micro model is linear (as it is with quadratic adjustment costs) and the aggregate model merely replicates the individual relationship, the resulting estimates suffer from aggregation bias. This means that the estimate of the parameter of the lagged dependent variable in the macro equation depends on both the corresponding and non-corresponding parameters of the micro equations. The aggregate speed of adjustment towards the steady state depends both on the firms technological parameters (particularly, the adjustment cost parameter) and on distributional issues (namely, the distribution of shocks within the aggregate). Hence, it will not be possible to infer the magnitude of adjustment costs from parameter estimates obtained with aggregate data as it will not be appropriate to link changes over time, or differences across countries, in the speed of adjustment to changes or differences in adjustment costs (Hamermesh, 1993a: 291).

If the true micro model is non-linear (as it is when adjustment costs are fixed) recoverability of the parameters of the micro model from aggregate data is

[1] The standard (although not unique) definition of aggregation bias is taken here. According to this the aggregation bias is just the difference between the parameters in the macro-equation and the corresponding micro-parameters (Theil, 1954).

possible only in very specific circumstances. Estimates of the parameters of non-linear models obtained with aggregate data should serve only to make aggregate predictions and will not, in any case, warrant behavioral interpretations.

In the study of labor demand, non-linearities in the form of a switching regression model arise from non-convex (fixed, e.g.) adjustment cost structures; in these cases, micro-level adjustment is typically large and infrequent. At the aggregate level the shape of the adjustment process depends on the degree of synchronization of the actions of the micro units. Micro and aggregate paths are similar when all the units are identical and take action simultaneously. Micro heterogeneity implies little synchronization and the possibility that the aggregate path of adjustment substantially differs from the corresponding micro paths (Caballero and Engel, 1991). [2] The less synchronized discontinuous individual actions are, the more the aggregate path resembles the smooth path generated by convex adjustment costs.

Fitting a partial adjustment model to aggregate data (under the assumption of convex costs and a representative agent) is expected to produce good statistical results even if the underlying micro pattern of adjustment is lumpy (Trivedi, 1985). But, if this is the case, the interpretation of the parameters in the usual partial adjustment way is incorrect. In particular, the coefficient of the lagged dependent variable will not measure the speed of adjustment to the long-run desired level nor will it be related to the magnitude of adjustment costs. In such cases, these parameters should only be interpreted as representing the proportion of units in the aggregate that are not changing employment (Hamermesh, 1990) or, for each unit, the fraction of the sample period it is inactive (Anderson, 1993).

Being able to use individual data is essential to avoid the problems caused by aggregation. But if we are interested in the study of dynamic relations, cross-sectional data sets are not appropriate. Nor are single time-series data sets as they suffer either from the problems of aggregation or from lack of generality. Their appropriateness to the study of dynamics (micro or macro) is, of course, one of the advantages of using panel data (Hsiao, 1986, Baltagi, 1995).

Full availability of micro data permits working either at the individual level, or at an aggregate level while incorporating all the relevant information on in-

[2] In non-linear models of employment adjustment there are three major sources of heterogeneity: location (differences in units' initial position within the inaction range), stochastic (presence of idiosyncratic shocks), and structural (differences in the widths of the inaction bands).

dividuals. In both cases, the problems of aggregation over cross-sections may be adequately dealt with. However, panel data does not necessarily avoid the problems associated with the aggregation over time. Temporal aggregation is known to imply biases in the estimates of dynamic models due to what essentially is a specification error. Taking a model that holds true for a certain time period and then again for the next does not necessarily imply that the model is true for the two periods together because the error term in each equation may have a different structure. Moreover, aggregation over time implies that part of the process of the lagged dependent variable is passed onto the error term, which further complicates its structure due to the inclusion of an additional component that is likely to be serially correlated. In addition to some technical difficulties, this also implies that the dynamic properties of the two models (that are identical in all respects but the underlying time unit) are different (Engle and Liu, 1972). One such difference has consequences again in terms of our ability to discriminate between different structures of adjustment costs.

Lower-frequency data is expected to bias the results against non-quadratic structures (Hamermesh, 1993b). Intuitively this makes sense. A distinctive implication of fixed adjustment costs is that changes in employment are typically large and infrequent. The probability of observing one single unit inactive is decreasing with the length of the observation period. In fact, temporal aggregation, just as spatial aggregation, smoothes away any signal of discontinuous adjustment that could be observed at the appropriate frequency.

The purpose of this paper is to investigate empirically the effects of spatial and temporal aggregation for the study of the dynamics of labor demand. The availability of a large panel of quarterly data collected at the establishment level provides the basic ingredient for this study. These data are, thus, aggregated across cross-sections (up to the 2-digit SIC industries) and temporally (up to the yearly frequency), and labor demand models corresponding to quadratic and non-quadratic adjustment cost structures are estimated at both frequencies (the two models) and at all cross sectional levels (the quadratic model).

The way aggregation is implemented here guarantees that, at whatever level or frequency we work, the exact same units are sampled. This is of course a necessary, if seldom met, condition to identify as aggregation biases all the differences the results may display. Except for the estimation of the model with fixed adjustment costs, standard panel data techniques are used in all the following empirical work.

The paper is outlined as follows. In section 2 the dataset is described. Next, the two competing models of labor demand are derived and the estimation strategy discussed (section 3). Estimates of the two models at different levels and frequencies are presented in section 4. Conclusions are outlined in section 5.

2 The Data

The data set used in this chapter samples 1,395 establishments in all industries except agriculture, fisheries and public administration. At the establishment level, data are available on the total number of employees as of the beginning and end of each quarter, and the total value of sales and wages.

This data set was constructed specifically for this purpose with data collected by the Portuguese Ministry of Employment based on two different surveys the Employment Survey (Inquérito ao Emprego Estruturado - IEE) and the Personnel Records (Quadros de Pessoal - QP). This was possible because, despite their different coverage and frequency, the two corresponding data files use the same ID number to identify each establishment surveyed.

The IEE contains data on quarterly employment counts but no information on wages or sales (or other proxy for production). In the QP data file there are information on employment, sales and wages but only at annual frequencies. For the purpose of this study it was essential to use data collected at least quarterly. For that reason the IEE data file was used as the master file for merge. Twenty waves of this survey from the first quarter of 1991 to the fourth of 1995 were available for this study.

A series of quarterly sales and wages then had to be generated. The QP data file was used for this purpose. Both quarterly series were constructed by interpolation of the corresponding annual data assuming smooth adjustment within each year. For the sales series, each quarters value corresponds to a weighted average of the current and previous years total sales with weights varying with the calendar quarter. [3] The value of sales assigned to each establishment in the QP data file is the total amount of sales of the firm the establishment belongs to. For the wage series, values were computed in a similar way but with different weights according to the timing of collective bargaining. [4] Annual sales and wage series were available from 1990 and 1991, respectively, to 1995.

[3]The value assigned to the $i-th$ quarter of year t corresponds to i times one fourth of the value of sales in year t value and $4-i$ the corresponding value in year $t-1$.

[4]In this case the value of the first quarter of year t corresponds to four times the quarterly average of year $t-1$ and is quarterly updated by one quarter.

Two data files were, thus, constructed with quarterly data, one with employment data and the other with sales and wages data. Merging the two using the establishments identification number was straightforward. The resulting file had 28,421 observations corresponding to an average of 1,776 establishments, covering 16 quarters. [5]

For the purpose of this chapter it is not essential that the sample used is representative of the population. What is required is that the sample used at all levels of aggregation (spatial and temporal) samples the exact same units. The merged file was thus used to obtain a balanced panel of establishments with information available for all the 16 quarters on both employment and sales and wages. Establishments with zero employment at any quarter were deleted from the sample. In the end a file with 1,395 establishments and 16 quarters was available for use in empirical work. Using a balanced panel was the preferred option because attrition would make it impossible to guarantee the compositional stability of the sample when data is aggregated over time.

3 Labor Demand Models under Competing Structures of Adjustment Costs

3.1 Quadratic Adjustment Costs

3.1.1 The Model

Assume a standard convex symmetric specification for the cost of adjustment function, as in Hamermesh (1989):

$$C(\dot{L}) = b\dot{L}^2 \tag{1}$$

The labor input is taken as homogeneous and adjustment costs are on net employment changes. L denotes the quantity of the labor input, the superior dot represents the variables rate of change and b is a nonnegative parameter. The firms optimization problem is one of maximizing the expected stream of its future total net profits (total profit, π, minus the adjustment costs) over the planning period. This writes as:

$$Max \qquad \pi(L) = \int_0^T [\pi(L_t) - b\dot{L}^2]e^{-\rho t}dt + \frac{\pi(L_t)e^{-\rho T}}{\rho} \tag{2}$$

[5] Because of the criteria set to compute quarterly wages, it was not possible to have data on these for the 1995 year. For this reason the four quarters of 1995 available in the IEE data file were dropped from the sample.

where ρ is the discount rate.[6] The corresponding Euler equation is:

$$\ddot{L} - \rho \dot{L} + \frac{\pi'(L)}{2b} = 0 \tag{3}$$

A closed-form solution is obtained by taking a linear approximation to this equation in the vicinity of the steady state. Solving the polynomial form associated to the difference equation thus obtained yields two characteristic roots, one of which (the one less than unity) is stable. Taking the general form of the solution to this difference equation and setting the unstable root to zero yields a flexible accelerator type solution of the form:

$$L_t = (1-\gamma)L_t^* + \gamma L_{t-1} \tag{4}$$

where γ is a nonlinear function of the parameters of the model (indeed, a positive function of b) and L^* is the long-run employment equilibrium level.

3.1.2 Estimation Procedure

Transition to empirical work implies specifying L^* in terms of observable variables. This is done by solving the firm's optimization program without adjustment costs (Bresson et al., 1992). If X_t is the vector of the determinants of the desired level of employment at time t (typically, some measure of production and factor prices), then we may write

$$L_{t+\tau}^* = \beta E_t(X_{t+\tau}^*) + \epsilon_{t+\tau} \tag{5}$$

Assuming expectations are rational and X follows an AR(1) process, the realized value of X at time $t+1$ may be substituted for its expectation formed one period ahead. Equation (2) thus becomes:

$$L_{it} = \alpha_0 + \alpha_1 L_{it-1} + \beta X_{it} + u_{it} \tag{6}$$

where β and X are vectors of parameters and covariates, respectively.

Assume the error term in equation (6) follows a one-way error component model,

$$u_{it} = \mu_i + v_{it} \tag{7}$$

[6] In essence, this is a free terminal state and free terminal time problem well known to the calculus of variations. The problem of the firm is to maximize the expected stream of profits over the adjustment period plus the present value of the profit rate at time T, which is essentially a problem of Bolza (Chiang, 1992).

where μ_i is an unobservable individual specific effect and v_{it} is an individual time-varying disturbance, with $\mu_i \sim IID(0, \sigma_\mu^2)$ and $v_{it} \sim IID(0, \sigma_v^2)$, independent of each other and among themselves.

Estimation of the dynamic panel data model described by (6) and (7) poses a number of difficulties because correlation between the regressors and the error is expected. This arises from the presence of the individual specific effect, which induces correlation between the error and the lagged dependent variable, and from the assumption of rational expectations, which raises correlation between the error and the other regressors due to a measurement error. [7] Violation of the assumption of uncorrelatedness of the regressors and the error leads to biased and inconsistent estimates if classical least squares methods are used. This is the reason why instrumental variable techniques such as the Generalized Method of Moments (Hansen, 1982; Hansen and Singleton, 1982) should, thus, be preferred.

Empirical implementation of this kind of models typically proceeds through first differencing the model and the subsequent use of first lags of the differenced or levels of the regressors as instruments (Anderson and Hsiao, 1981). In the empirical literature, instruments in levels for the model in first differences is the preferred alternative. This should produce consistent but not necessarily asymptotically efficient estimates. For the model in first differences, additional instruments can be obtained by exploiting the orthogonality conditions between lagged values of the dependent variable and the regressors (if these are predetermined) and the error (Arellano and Bond, 1991).[8]

3.2 Fixed Adjustment Costs

3.2.1 The Model

If the costs the firm incurs at when changing the (net) quantities of the labor input are invariant with respect to the magnitude of the change and identical in expansions and contractions, then a fixed symmetric structure is the appropriate specification for the adjustment cost function of the firm.

A function of this type is:

[7]Rational expectations imply substituting the realized value of the regressors plus an error term for their expectations. Such error is, in fact, a measurement error that merges with the disturbance of the original model. As a consequence correlation between the regressors and the residuals should be expected.

[8]Given that the validity of these instruments relies on the assumption that the residuals are not serially correlated, it is essential that serial correlation is tested for when this method is used.

$$C(\dot{L}) = \begin{cases} k & \text{if } |\dot{L}| > 0 \\ 0 & \text{if } |\dot{L}| = 0 \end{cases} \quad (8)$$

where k, the adjustment cost, is non-negative.

Embedding this cost function in the objective functional describing the firm's optimization problem (2) originates a well-known situation in the optimal control literature. The discontinuity in the adjustment cost structure makes the Hamiltonian non-differentiable in the control variable. As a result, only corner solutions are admissible. In practice, this means that each period the firm compares its current level of employment to its equilibrium value and decides whether to move to its long-run equilibrium or not. If profits increase enough to overcome the fixed costs of adjusting employment, then the firm optimally chooses to adjust to the equilibrium level of employment fully and instantaneously. If not, the firm chooses not to act and employment remains unchanged.

In this case, the labor demand path can be described by:

$$L_t = \begin{cases} L_{t-1} + \mu_{1t} & \text{if } |L_{t-1} - L_t^*| \leq K \\ L_t^* + \mu_{2t} & \text{if } |L_{t-1} - L_t^*| > K \end{cases} \quad (9)$$

This is essentially a switching model in which the firm switches from inaction to action as the absolute deviation of the current level of employment from its equilibrium level changes from less to more than K. K is a nonnegative parameter positively related to the magnitude of the fixed cost of adjustment (k).

3.2.2 Estimation Procedure

Transition to empirical work implies again specifying L^* in terms of observable variables. Assume

$$L_t^* = aX_t + \epsilon_t \quad (10)$$

where a is a vector of parameters, X is a vector of variables that affect L^*, and ϵ is an error term. Substituting (10) for L^* in (9) induces a transformation of the disturbance term, which becomes:

$$\mu_2^{'} = \mu_2 + \epsilon \quad (11)$$

Empirical implementation of (9) and (10) depends on whether sample separation is known or unknown (Goldfeld and Quandt, 1976; Maddala, 1986).

Sample separation may be assumed known if an appropriate indicator is available. In this case, the separation dummy variable, I, is observed and writes as:

$$I = \begin{cases} 1 & \text{iff } -K + (L_{t-1} - aX_t) \leq \epsilon \leq K + (L_{t-1} - aX_t) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where μ_1, μ_2, and ϵ are assumed to follow a normal trivariate distribution with mean zero and matrix of variances and covariances Σ defined as:

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1\epsilon} \\ \sigma_{12} & \sigma_{22} & \sigma_{2\epsilon} \\ \sigma_{1\epsilon} & \sigma_{1\epsilon} & 1 \end{bmatrix} \tag{13}$$

It is further assumed that σ_{12} and $\sigma_{1\epsilon}$ are equal to zero, implying that the inaction regime is observed without error. In this case, the likelihood function is:

$$l = \prod \left[g_1(\mu_1) \int_{-K+(L_{t-1}-aX_t)}^{K+(L_{t-1}-aX_t)} f_1(\epsilon|\mu_1) d\epsilon \right]^I \left\{ g_2(\mu_2^{'}) \left[1 - \int_{-K+(L_{t-1}-aX_t)}^{K+(L_{t-1}-aX_t)} f_2(\epsilon|\mu_2^{'}) d\epsilon \right] \right\}^{1-I}$$

(14)

where $g_1(\mu_1)$ and $g_2(\mu_2)$ are the marginal densities, and $f_1(\epsilon|\mu_1)$ and $f_2(|\mu_2)$ are conditional densities.

The corresponding log-likelihood function for this model is obtained by summation over all units and time-periods. Estimation of this model implies that, as with probit models, the parameter K is estimable only up to a factor scale, for which reason σ_ϵ was normalized to 1. σ_{12} does not occur in the likelihood equation and is not estimable. Incorporating individual specific effects in this case is not trivial. Individual specific dummies would result in 1,394 parameters in each equation, which is computationally very demanding. Alternatives to this were offered before in similar contexts, although none is deemed satisfactory (Hu and Schiantarelli, 1998). One such alternative, using the establishments pre-sample history to control for the unobserved heterogeneity, is not an option here because it is essential for the purpose of this study to estimate this model with the same dataset used for the quadratic model. Hence, the model with fixed adjustment costs is estimated with the pooled dataset only.

4 Empirical Results

4.1 Results with Individual and Quarterly Data

4.1.1 Quadratic Adjustment Costs

The natural starting point for the study of the effects of spatial and temporal aggregation is the lowest cross-sectional level and lowest frequency available (in this case, the establishment and the quarter). The estimates produced with such data for the model with quadratic adjustment costs are reported in Table 1. [9] In addition to the first lag of the dependent variable, the logs of sales and wages and time dummies were also included as regressors. Test statistics for the validity of the instruments (Sargan test) and for the lack of first and second order serial correlation (m_1 and m_2 tests) are reported. The model was estimated both in levels using instruments in first-differences and in first-differences using instruments in levels GMM-Sys estimator. [10]

The estimate of the coefficient of L_{-1} is 0.961 implying an overly large median lags of adjustment (17.4 quarters with the GMM-Sys estimator). The elasticity of employment with respect to both sales and wages have the right sign but are very low and not significant at 10 percent in the case of the wage elasticity. These results are satisfactory since they imply the distribution of adjustments over a long period and very low short-run elasticities. As mentioned, the small values of the parameters estimates may be the result of wrongly assuming equal coefficients for the regressors. (Robertson and Symons, 1992). [11]

4.1.2 Fixed Adjustment Costs

The same sample that produced the results in Table 1 was used to estimate the switching regression model on the basis of the assumption of fixed adjustment costs.

Taking the actual variation in employment (or its absence) as the indicator used for assigning each observation to the action and inaction regimes, the model

[9] DPD98 for Gauss was used to estimate this model (see Arellano and Bond, 1998). All results for the quadratic adjustment case reported in this chapter refer to the model in the logarithmic form.

[10] For details, see Arellano and Bover (1995).

[11] The results in Robertson and Symons (1992) results were obtained for a panel with a relatively large number of units (50), few time periods (5) and a coefficient of serial correlation of residuals of 0.5. The dataset used in this study is considerably larger (1395 establishments and 15 quarters).

Variable	Coefficient	Standard Error
L_{-1}	0.961	0.006
Sales	0.007	0.002
Wages	-0.009	0.007
Time Dummies	Yes	
Sargan	143.4	
m_1	-8.1	
m_2	0.4	

Table 1: Estimates for the Quadratic Adjustment Costs Model: establishment-level, quarterly data (N=1395, T=14) GMM-Sysl. Instruments used are: $\Delta N_{-4}...\Delta N_{-14}$, $\Delta Sales_{-3}$, $\Delta Wage_{-3}$, N_{-3}, $Sales_{-2}$, $Wage_{-2}$. .

may be estimated assuming sample separation known.[12]

The estimates obtained (Table 2) are all significant at 1 percent and have the right sign. Besides, they all compare fairly with the estimates available from other studies, even if the two elasticities are larger than what is usually reported (see Hamermesh, 1989). [13]

Although individual effects were not accounted for in the estimation of the switching model, this offers reasonable and statistically significant estimates of the parameters, indicating that the fixed adjustment cost structure fits the data quite well. Put differently, there are clear signs of non-linearities in employment adjustment.

4.2 Temporal Aggregation of Establishment-level Data

4.2.1 Quadratic Adjustment Costs

The model with quadratic costs of adjustment was also estimated with annual data, using the same dataset but selecting observations four quarters apart. Results are shown in Table 3.

The estimated coefficient of L_1 is 0.904, which implies an unreasonably long

[12] This is, of course, a stringent assumption. However, if we assume sample unkown, we get similar results.

[13] Hamermeshs estimate obtained with a pooled data set is approximately 0.6 with actual values ranging from 0.031 to 1.040. The estimate obtained here is clearly outside this range, although the estimates for the sales (product) elasticity are not. Remember that the estimates of K are not strictly comparable across studies because the estimate of K is actually an estimate of K/σ_ϵ and σ_ϵ was normalized to unity).

Variable	Coefficient	Standard Error
Sales	0.409	0.003
Wages	-0.669	0.018
Time	-0.005	0.002
K	0.889	0.007
σ_{22}	1.221	0.008
$\rho(\mu_2, \epsilon)$	-0.663	0.012
Log Likelihood	-35255.8	
Nr. Observations	20925	

Table 2: ESTIMATES FOR THE FIXED ADJUSTMENT COST MODEL: ESTABLISHMENT-LEVEL, QUARTERLY DATA (N=1395, T=15). SAMPLE SEPARATION KNOWN THIS MODEL WAS ESTIMATED IN THE LOGARITHMIC FORM.

median lag of adjustment (27.5 quarters). This exceeds all the estimates available for annual data (Hamermesh, 1993a, Table 7.1), with few exceptions. The most notorious of these exceptions, using micro annual data on employment, are the studies by Jones and Pliskin (1989) that reports an estimated median lag of 26.3 quarters, and Blundell and Bond (1998), which also used a GMM-Sys estimator an obtained an estimated median lag of 18.3 quarters.

Although temporal aggregation does not imply a priori any bias in the estimated lag of employment adjustment, studies using annual data generally imply longer lags. The only study that uses the same dataset to estimate (at the industry level) an employment equation at three different frequencies (monthly, quarterly, and annual frequencies) reaches mixed results, although in most cases the aggregate estimates are upward biased (Hamermesh, 1993b). This is consistent with the results reported here.

Longer estimated adjustment lags may result from temporal aggregation (from quarterly to annual frequencies) for two different reasons. First, temporal aggregation induces positive serial correlation of the residuals and, therefore, an upward bias in the estimate of the coefficient of the lagged dependent variable (Engle and Liu, 1972). Second, using annual data generally implies shorter panels. In these cases we have for the quarterly panel N=1395 and T=14, and for the annual panel N=1395 and T=3. Although typical panel data sets used in labor economics have a large number of individuals and few time periods, when we move from higher to lower frequency panels that characteristic is exacerbated,

Variable	Coefficient	Standard Error
L_{-1}	0.904	0.035
Sales	0.011	0.010
Wages	-0.032	0.043
Time Dummies	Yes	
Sargan	18.7	
m_1	-4.5	
m_2	n.a.	

Table 3: ESTIMATES FOR THE QUADRATIC ADJUSTMENT COSTS MODEL: ESTABLISHMENT-LEVEL, YEARLY DATA (N=1395, T=3) GMM-SYS. INSTRUMENTS USED IN THIS CASE ARE: N_{-3}, $Sales_{-2}$, $Sales{-}3$, $Wages_{-2}$, $Wages_{-3}$, ΔN_{-2}, $\Delta Sales{-}1$, $\Delta Wages_{-1}$.

making the specification error problem discussed by Robertson and Symons (1992) more serious.

The estimates of the short-run elasticities of employment with respect to sales and wages still very low and barely or not at all, significant. Even though regression coefficient estimates for both sales and wages, specially for wages, are slightly larger and more reasonable than those obtained with quarterly data, their precision is smaller, as expected.

Be as it may, low estimates of the two elasticities are consistent with the results of Robertson and Symons (1992) for this kind of dataset and estimation procedure. However, they may also be an inevitable by-product of temporal aggregation. Due to the panels shorter length, the number of potential instruments is severely reduced leaving no option other than using all the lags available. This inevitably results in less, and less than adequate, instruments. This is clearly illustrated by the results of the Sargan test reported in Table 3, which lead to the rejection of the null-hypothesis at a significance level of 5 percent, and is consistent with the presence of measurement errors.

4.2.2 Fixed Adjustment Costs

The switching regression model was also implemented with annual data with the same cross-sectional composition underlying quarterly estimates previously discussed. Results are reported in Table 4.

As for quarterly observations, all the coefficient estimates are significant and have the correct sign. Estimates of the coefficients of sales and wages obtained with annual data are very similar to the quarterly ones. Temporal aggregation up to the annual frequency did not produce substantial effects on the estimates of the parameter K either estimates using annual data are the same as those obtained with quarterly data (0.869). [14]

The most apparent sign of temporal aggregation following from the comparison of Tables 2 and 4 is the reduced precision of all the estimates resulting from annual data. Apart from this effect, the dynamics of labor demand conveyed by the results obtained are virtually unchanged by temporal aggregation.

Variable	Coefficient	Standard Error
Sales	0.418	0.006
Wages	-0.706	0.035
Time	-0.031	0.012
K	0.869	0.014
σ_{22}	1.800	0.228
$\rho(\mu_2, \epsilon)$	0.194	0.012
Log Likelihood	-9418.86	
Nr. Observations	5580	

Table 4: Estimates for the Fixed Adjustment Cost Model: establishment-level, yearly data (N=1395, T=4). Sample Separation Known. This model was estimated in the logarithmic form.

Considering the theoretical implications of aggregation over time this result is quite surprising. Temporal aggregation is expected to bias the estimates against non-linear models because it implies that all the activity is, partly or fully, reversed within the course of one year is missed by annual data, just as employment changes reversed within quarters are missed by quarterly data. Our results may simply arise from employment adjustment being highly persistent in the Portuguese labor market, which implies that temporal aggregation does not miss as much information as when net employment adjustment is reversed more frequently, as may seem in other labor markets.

It is however surprising to find that the coefficient of the sales elasticity is

[14] Notice, however, this comparison is clouded by the fact that the K parameter is in both cases estimable only up to a scale parameter, estimates obtained with different datasets are not strictly comparable.

not significantly affected by temporal aggregation, mainly because the quarterly data on sales is measured with error. As discussed before this could be expected to bias downwards the estimates of the sales elasticity obtained with quarterly data, which does not actually show in the results.

4.3 Spatial Aggregation of Quarterly Data [15]

To study the effects of spatial aggregation on the estimation of the labor demand equation, the quarterly establishment-level dataset was used as the basis upon which increasingly aggregated (over individuals) datasets were constructed. Three different datasets, corresponding to three different cross-sectional levels (from the establishment up to the 2-digit industries), were thus made available for empirical work. The results of estimating the demand equation at these different levels are reported in Table 5. The estimates reported were obtained with the GMM-Sys estimator. Results for the establishment level, reported in Table 1, are reproduced in the last column of Table 5.

At the level of the establishment, all coefficients have the right signs although for reasons discussed above they are biased towards unity in the case of the coefficient of L-1 and towards zero in the case of the remaining regressors.

Increasing aggregation over individuals of quarterly data does not produce any systematic results. From the establishment to the 6-digit industry level, the estimated median lag of adjustment and the coefficient of sales both become more reasonable (shorter lags and larger sales elasticity). However, the wages elasticity becomes positive and statistically significant.

The results obtained at the 2-digit industry level must be emphasized. The estimation of the coefficient of the lagged employment variable obtained at this level of spatial aggregation is perfectly reasonable in terms of the corresponding median lag length. This is indeed the most reasonable estimate we obtained at every frequencies and cross-sectional levels considered. At this cross-sectional level, the long-run output elasticity is too large and the long-run wage elasticity is even larger but, in any case, both have the right sign. This result differs from the best estimates obtained at the establishment level, in which case the lag length is too long and the long-run output elasticity is too small.

[15] The effects of spatial aggregation are investigated empirically in this section for the quadratic adjustment cost model only. The purpose of this chapter is to investigate the implications of using inappropriate data (either in terms of cross-sections or time periods). Of all the few studies that estimate a switching regression model of labor demand (Hamermesh, 1989, 1993b; Rota, 1994) none uses spatially aggregated data.

	2-digit SIC		6-digit SIC		Establishment	
Variable	Coeff	SE	Coeff	SE	Coeff	SE
L_{-1}	0.834	0.078	0.938	0.0001	0.961	0.006
Sales	0.290	0.159	0.037	0.0001	0.007	0.002
Wages	-0.796	0.494	0.015	0.0002	-0.009	0.007
Time Dummies	Yes		Yes		Yes	
Sargan	8.6		272.7		143.4	
m_1	3.9		-4.1		-8.1	
m_2	-0.7		-0.6		0.4	
Units	26		287		1395	
Time periods	14		14		14	

Table 5: Estimates for the Quadratic Adjustment Costs Model-quarterly data. GMM-Sys. Instruments used in this case are: $N_{-4}...N_{-14}$, $Sales_{-3}$, $Wages_{-3}$, ΔN_{-3}, $\Delta Sales{-2}$, $\Delta Wages_{-2}$.

In all regressions, the test statistics reported in all cases generally verify the critical assumption of no second-order serial correlation (m2 test) and the validity of the instruments (Sargan test).

We may conclude, therefore, that, with high-frequency (quarterly) data, passing from the establishment level to higher levels of aggregation appears to originate more reasonable for the quadratic adjustment cost model results that show up in several ways.

5 Conclusion

The case against the use of spatially and temporally aggregate data in studies of labor demand dynamics has been made before, although always theoretically. No empirical study attempted at a detailed treatment of the effects of aggregation using the same data set aggregated at different cross-sectional levels and time frequencies. This was the purpose of this paper.

Even though no panel data techniques were used, the switching regression model corresponding to the assumption of fixed adjustment costs performed quite well, indicating the presence of important non-linearities in the employment path at the micro level. This is this paper's first contribution. The estimated elasticities of labor demand with respect to both wages and sales obtained with this specification are in line with those reported in the literature and much more sensible than the corresponding estimates obtained with the quadratic model at the same level of aggregation.

The performance of the standard labor demand model with quadratic adjustment costs is affected by the assumption of common regressors coefficients across cross-sections. The results clearly indicate that the consequences of this specification error should not be overlooked.

Although aggregation over individuals has mixed effects on the estimates obtained with the quadratic adjustment cost model, because it smoothes the pattern of adjustment and results in smaller panels, the best overall results were obtained with annual two-digit data: the coefficient of the lagged dependent variable is around 0.9 (which is large but not as much as in other cross-sectional levels) and the two elasticities are quite reasonable. Temporal aggregation works in the same direction - estimates of the parameters of the quadratic adjustment cost model are more sensible if yearly data, as opposed to quarterly data, are used .

We conclude that the validity of the assumption of quadratic adjustment costs should not be judged by the quality of the results obtained with the partial adjustment model alone, even at the individual level. A comparison of these results against those corresponding to fixed (or other non-quadratic) adjustment costs structures is required. In any case, progress is yet to be made on the estimation of non-linear models that appropriately incorporate unobserved individual heterogeneity.

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