Labor Adjustment Dynamics in Brazilian Manufacturing*

Gustavo Gonzaga**

Abstract

In this paper, we investigate the dynamics of labor adjustment at the firm level in Brazilian manufacturing, using information on average hours per worker to measure employment deviation from desired levels as in Caballero et al. (1997). We use Brazilian manufacturing data at the establishment level and monthly frequency. The objective is to estimate the employment adjustment function, which relates the magnitude of employment changes to the size of employment gaps. The empirical results point to the presence of nonconvexities in employment adjustment costs in Brazilian manufacturing, with estimated employment adjustment rates increasing with the size of employment gaps. On average, employment adjustment rates range from 10% for small employment gaps to 35% for large ones. The results also show that there is a large proportion of firms in the sample that do not adjust employment over two consecutive periods. We run several robustness tests with alternative ways of estimating the employment gaps, using other forms of dealing with measurement error and a problem of endogeneity of the hours change variable. Although the magnitudes of employment adjustment rates vary, we show that: i) the variations are in line with the expected directions of the biases in estimating the coefficient of the hours change variable; and ii) the format of employment adjustment functions does not change across specifications, always revealing that employment adjustment rates increase with the size of employment gaps, which is compatible with nonconvex costs of employment adjustment. We also study how the employment adjustment function varies according to several establishment characteristics, such as skilled-labor intensity, size, payroll expenses, and overtime payments. We show that the employment adjustment function tends to have a higher mean and to display larger values when measured for establishments with characteristics that are arguably related to lower costs of employment adjustment: larger proportion of low-skilled workers, smaller size and lower overtime payments.

Keywords: Labor Adjustment Dynamics, Nonconvex Employment Adustment Costs.

JEL Codes: J23.

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**Department of Economics, PUC-Rio. E-mail: `gonzaga@econ.puc-rio.br`

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1. Introduction

Some authors have claimed that evidence from less developed countries could shed some light on the understanding of employment adjustment dynamics at the firm level, since these countries are often more exposed to massive aggregate and idiosyncratic shocks. Brazil fits this description: since 1985, Brazilian firms have been exposed to many structural reforms and inflation stabilization attempts.

In this paper, we study the dynamics of labor adjustment at the firm level in Brazilian manufacturing. We follow the methodology proposed by Caballero et al. (1997), hereafter referred to as CEH, applied to Brazilian data at a monthly frequency. Information on hours paid is used to construct a proxy for the unobserved desired level of employment and to obtain an estimate for the employment gap, defined as the difference between actual and desired employment levels.

The objective of the study is to estimate the employment adjustment function, which relates the magnitude of employment changes to the size of labor shortages. The identification of the form of the employment adjustment function can uncover important aspects of microeconomic employment dynamics and shed more light on the nature of employment adjustment costs, such as the presence of nonconvexities and asymmetries. In particular, we analyze how the employment adjustment function varies according to several establishment characteristics, such as skilled-labor intensity, size, payroll expenses, and overtime payments.

Many authors have shown that one of the main characteristics of the Brazilian labor market is a very high labor turnover rate (see, for example, Amadeo and Camargo (1996), and Gonzaga et al. (2003)). Although the Brazilian labor code is very restrictive, dismissal costs are not high relative to other Latin American countries. Some authors even argue that the design of some job security programs creates perverse incentives that generate labor turnover.

A better understanding of microeconomic employment dynamics is, therefore, an important piece of information that could complement the analysis of labor turnover. Barros et al. (2001), for instance, estimated partial adjustment labor demand equations for the manufacturing sector using the same dataset as the one used here, and found a very high speed of employment adjustment. Jacinto and Ribeiro (2009) found evidence in favor of non-convex costs of employment adjustment using microeconomic manufacturing data for the state of Rio Grande do Sul. In this paper, we use a more flexible empirical approach in order to estimate employment adjustment functions and to shed further light on the dynamic process of joint determination of hours and employment.

Cooper and Willis (2004a), hereafter referred to as CW, show that the methodology used by CEH applied to artificial data generated from a model with quadratic adjustment costs generates a nonlinear employment adjustment function, contrary to a constant employment adjustment function, which would be expected with this form of adjustment costs. They argue that this occurs because the employment gap, estimated by CEH using information on hours changes, is mismeasured.

The main source of mismeasurement is the correlation between hours changes and shocks to desired employment, which are respectively the explanatory variable and the error term in a regression with employment changes as the dependent variable, a crucial step in the CEH methodology.

In an exchange of articles about the subject in an American Economic Review issue, Caballero and Engel (2004) rebut these claims as either wrong or irrelevant, for reasons discussed in more detail below. More important for our objective in this paper, Cooper and Willis (2004b) and Caballero and Engel (2004) agreed that there is wide consensus in the literature that employment adjustment is lumpy at the microeconomic level, in which case applying the CEH methodology would not be wrong.[1]

In this paper, we show evidence that microeconomic employment adjustment in Brazilian manufacturing is also lumpy. We then use CEH methodology to estimate employment adjustment functions and to learn more about employment dynamics at the firm level. In order to deal with some of the CW criticisms, we run several robustness tests with alternative ways to deal with the problems of measurement error and the bias coming from a possible correlation between small variations in hours and desired employment levels. Our results help clarify some of the issues raised by CW with respect to the magnitude and direction of the bias in the regression of employment variation on hours changes when using only observations with large changes as suggested by CEH. More important for our purposes here, we show that these alternative ways of dealing with the problem of endogeneity of hours changes do not affect our main conclusions with regard to the dynamics of employment adjustment at the micro level.

Moreover, the paper contributes to the empirical literature on the dynamics of employment adjustment by using higher frequency (monthly) unbalanced data for a developing country,[2] and by performing a more thorough analysis of how firms' characteristics affect the format of the employment adjustment function. The use of fixed effects to control for time-invariant unobserved heterogeneity in the estimation of how employment changes relate to hours changes, a crucial aspect of the CEH methodology, is also an innovation of the paper.

For operational reasons, the paper uses data ending in 1998. However, there were no major changes in the Brazilian labor legislation since the Constitution of 1988, especially with respect to employment adjustment costs. Therefore, we believe that the main results we find reflect structural characteristics of the Brazilian labor market, and should not significantly change with the use of more recent

[1] As discussed by the authors, the criticism in CW would be more important for someone interested in uncovering the implications of microeconomic employment dynamics for the **aggregate** employment dynamics.

[2] Most analyses of employment adjustment use quarterly or annual data that may hide important employment rigidities occasionally present in less temporally aggregated data (Hamermesh and Pfann, 1996). Our analysis is also not restricted to firms that existed throughout the sample period as is common in other studies of employment adjustment.

data.

The paper is organized as follows. Section 2 provides an overview of the methodology used to measure the employment gap and the employment adjustment function, and discusses its limitations. Section 3 presents the descriptive statistics of the dataset. Section 4 presents the empirical results. Section 5 provides the main conclusions of the paper.

2. Methodology

2.1 Estimating employment adjustment functions

Until the early 1990s a strictly convex and symmetric function was the conventional assumption used in the literature to describe the structure of employment adjustment costs. While the convex structure has been widely used mainly because of its analytical convenience, some could defend it based on arguments of internal reorganization costs (Hamermesh and Pfann, 1996). The idea behind it is that the disruption caused by the introduction of new hires (the dismissal of current workers) could increase costs more than proportionally with respect to the number of workers hired (fired) leading to convex, usually quadratic, adjustment costs.

In part inspired by the evidence that employment adjustment at the firm level is lumpy (Hamermesh, 1989), which contrasts with the pattern of continuous adjustment implied by convex labor demand models, a branch of the literature pursued a deeper investigation of the empirical implications of linear and fixed costs of adjustment as alternative structures for the employment adjustment cost function.[3]

In particular, Caballero and Engel (1993) and Caballero et al. (1997) proposed alternative empirical methodologies to examine the presence of nonconvexities in the data. The idea is to estimate employment adjustment functions in which the probability of employment adjustment depends on the size of the employment gap – the distance between the desired and the actual level of employment. One of the advantages of this approach is that it encompasses both structures of adjustment costs (quadratic and linear/fixed) enabling one to test which one best describes the data. The standard quadratic adjustment cost model, for example, implies a constant employment adjustment function, in which employment adjustment does not depend on the size of the employment gap. In contrast, linear or fixed adjustment costs imply a nonlinear employment adjustment function, in which the probability of labor adjustment increases with the size of the employment gap.[4]

[3]See Bentolila and Bertola (1990) and Bertola (1990) for the implications of linear or fixed adjustment costs for optimal employment paths chosen by profit-maximizing firms.

[4]See Bond and Van Reenen (2007) for a survey of the literature on capital and employment adjustment using microeconomic data. In particular, they review recent attempts to measure the employment gap by using "a more explicit structural approach to address the issues of non-convex adjustment costs." Hamermesh (1993) and Hamermesh and Pfann (1996) are other less recent excellent surveys on the issue.

Since the desired level of employment is an unobservable variable, the main challenge for this literature is to find a good proxy for the employment gap. Based on considerations that hours adjust faster than employment, since hours are less costly to adjust than employment, Caballero et al. (1997) proposed the use of the distance of current hours from a long-run target as a measure of labor shortage. The idea is that if the desired number of employees is above the current employment level, because of employment adjustment costs, an optimizing firm should choose to increase the number of hours of its workers, which is supposedly a less costly alternative. Therefore, they propose to measure the current employment gap (after adjustments have been made) by:

$$z_{it}^1 = e_{it}^* - e_{it} = \theta_j(h_{it} - \bar{h}_i) \tag{1}$$

where e_{it}^* and e_{it} are, respectively, the desired and actual employment levels; h_{it} represents hours per worker; $\bar{h}_i$ is the sample average of hours per worker; θ_j is a parameter assumed to vary by sector; i indexes firms, t indexes time, and j indexes sectors.

In order to estimate θ_j, one could take first differences from both sides of equation (1) to note that:

$$\triangle e_{it} = -\theta_j \triangle h_{it} + \triangle e_{it}^* = -\theta_j \triangle h_{it} + \varepsilon_{it} \tag{2}$$

where the last term is an unobserved shock. Adding a constant, one could estimate $\hat{\theta}_j$ by OLS pooling data for each sector.

However, as noted by the authors, one should expect to get biased estimates of θ_j coming from the OLS estimation of equation (2), since the error term (a shock to desired employment) is likely to be correlated with hours changes, at least in the short run. The presence of employment adjustment costs implies that a part of the shock is accommodated by hours changes. In order to deal with this problem, the authors propose to only use observations in which both employment and hours changes are larger (in absolute value) than one standard deviation of the respective series. The argument is that large adjustments of hours and employment would "overwhelm the error," especially when employment adjustment is lumpy (see CW).

Even then there would still be a potential measurement error bias, which they (partially) handle by estimating equation (2) in both its normal ($\triangle e$ on $\triangle h$) and reverse ($\triangle h$ on $\triangle e$) orders. Since it is known that the normal order regression yields a downward biased estimate and the reverse order regression yields an upward biased estimate, the authors propose to use the convex combination of the two coefficients (from the normal and reverse order equations), which minimizes the mean square error of the estimate of each sectoral $\hat{\theta}_j$.

An additional source of concern in the Brazilian case is that the standard workweek was reduced from 48 to 44 hours as prescribed by the Constitution of

1988 (Gonzaga et al., 2003). Since it is expected that optimizing firms have reacted to it by changing their choices of hours and employment, we estimate θ_j separately for the periods before and after the new Constitution. We chose all months before August 1988 as representing the period before the new Constitution (implemented in November 1988) and all months after January 1989 as the period after the new Constitution.

The pre-adjustment employment gap is then easily obtained by plugging the estimated $\hat{\theta}_j$'s in each period (pre and post 1988) into equation (1) and adding $\triangle e_{it}$ to get:

$$z_{it} = e^*_{it} - e_{i,t-1} = \hat{\theta}_j (h_{it} - \bar{h}_i) + \triangle e_{it} \tag{3}$$

The employment adjustment function is obtained by dividing employment changes (first differences of log employment) by employment deviations, z.[5] This function can be interpreted as the proportion of the employment gap that is closed by employment adjustment in each period. To deal with structural changes related to the new Constitution of 1988, pre and post 1988 periods are separately used to compute average hours per worker.

In Section 4, we apply this adapted methodology to Brazilian data in order to study the dynamics of employment adjustment in Brazilian manufacturing firms. In particular, the methodology allows us to detect the presence of non-convex employment adjustment costs in Brazilian firms, to study asymmetries in employment adjustment, and to analyze how the employment adjustment function is affected by firm characteristics.

The methodology can be summarized as follows:

i) we first estimate θ_j using the procedure described above for each of the 22 Brazilian manufacturing sectors for the periods before and after the Constitution of 1988;

ii) we then use equation (3) to measure the employment gap for each firm in each month in the sample period;

iii) we finally compute the employment adjustment rate by dividing $\triangle e_{it}$ by z_{it} and plot the average employment adjustment function.

2.2 Limitations of the methodology and proposed changes

Before we move on we should stress some limitations of the CEH methodology. As mentioned above, CW show that the employment gap measure obtained with the CEH methodology is mismeasured and does not correspond to the true employment gap in simulated data coming from a quadratic adjustment cost model.

[5] We use equally spaced grids of 0.02, with z_{it} varying from -4.0 to 4.0.

Moreover, they show that the methodology generates a nonlinear employment adjustment function, contrary to a constant employment adjustment function, which would be expected given the partial adjustment model used to create the data.

They then argue that the method is not suitable to test the quadratic model because this model would imply a more frequent and small employment adjustment, which is incompatible with the use of observations with large changes as in the first step of the CEH methodology, the estimation of θ in equation (2), a regression of employment changes on hours changes. Their main criticism, which CEH in fact tried to correct as discussed above, was that the hours changes variable is correlated with the error term, the shocks to the employment target level. The point CW correctly made was that if the data were in fact generated from a quadratic adjustment model, there would be **no large** observations of employment changes, since in this case employment adjustment would be more continuous. In a reply article, Caballero and Engel (2004) rebut these claims as irrelevant, because no sensible research would use their procedure if the data were not lumpy.

In Section 4 below, we show evidence that microeconomic employment adjustment in Brazilian manufacturing is also lumpy, which encouraged us to use the CEH methodology to estimate employment adjustment functions. Nonetheless, the endogeneity problem discussed above requires more effort from us to correctly estimate θ, or at least to study the magnitude and direction of the estimation bias. We also discuss the sensitivity of the results with respect to alternative ways of dealing with this problem.

In particular, we adapt the CEH methodology for estimating equation (2) in three ways. First, we estimate equation (2) for all sectors using firm fixed effects in order to control for time-invariant unobserved heterogeneity.

Second, we run robustness tests with alternative ways to deal with the problem of measurement error. As discussed above, it is known since Leamer (1978) that the use of the normal and reverse order regressions are useful for identifying lower and upper bounds of θ, since measurement error produces an attenuation bias. The CEH proposal of using a convex combination of the bounds, one that would minimize the mean-squared error of θ, was somewhat arbitrary as any other. In this paper, we also estimate employment adjustment functions which would be obtained if one uses the biased estimates of θ, from the normal and reverse order regressions. We discuss in Section 4 how sensitive the results are with respect to the use of the bounds themselves, instead of their convex combination.

Third, as noted above, there is a bias in the estimation of θ coming from a possible correlation between variations in hours and employment, when changes are small, since shocks to desired employment (the error term) are possibly correlated with changes in hours. Therefore, if one uses all observations to estimate equation (2), the coefficient $-\theta$ would be overestimated, that is, θ would be closer to zero, in absolute value. In the absence of a good instrument, CEH proposed to use only observations of large changes (above one standard deviation) in hours and employment, arguing that during the episodes of large adjustments, "the variability of the regressor swamps the variability of the error term in that regression" (Caballero and Engel, 2004). In order to further study this issue, in subsection 4.3, we also estimated equation (2) using more stringent filters (above two standard deviations) and more flexible filters (above half a standard deviation and using all observations).

A final source of concern is the hypothesis that the costs of adjusting hours are lower than those of adjusting employment. In Brazil, there is evidence that the costs of adjusting hours are higher than those of adjusting employment at least in some sectors. In the limit, if costs of adjusting hours were infinite, hours would be constant and could not be used to infer the level of desired employment. In this case, the estimated θ's would be zero, which implies that the employment adjustment rate would equal one for all values of z. In this case, the interpretation that firms were quickly filling employment gaps would be wrong. On the contrary, there would not be employment gaps to be filled at least as measured by this methodology.

Positive estimated θ's mean that, at least in some sectors, hours are less costly to adjust than employment. Note that small θ's and hours close to average hours also generate employment adjustment functions around one. However, even in this case, the form of the employment adjustment function can vary over the values of z, which provides important information about the structure of employment adjustment costs. Therefore, the estimation of equation (2), whose results are reported in subsection 4.1, is crucial for correctly interpreting the form of the employment adjustment function.[6]

3. Data and Descriptive Statistics

We use information from firm data for the industrial sector in Brazil taken from *Pesquisa Industrial Mensal (PIM)*, a monthly establishment survey that covers the entire country, conducted by IBGE (the Brazilian Census Bureau). *PIM* is a longitudinal survey of a stratified sample of 4,500 manufacturing establishments employing five workers or more. The original panel was selected in mid-1984, together with a supplementary sample chosen to replace establishments in the panel that eventually close. The panel covers the period from January 1985 to December 1997. The sample was originally designed to allow most of the statistical analysis to be conducted by breaking Brazil down into six geographical areas and 22 manufacturing sectors.

The survey collects data on labor inputs, labor costs, turnover (number of hires and separations), and value of production for each firm. The information on labor inputs covers both employment and the total number of hours paid. All data refer to production workers and there is no information on labor qualification.

[6]Note that other less costly unobservable margins, such as effort, could certainly provide more information on desired employment, but we have no information on them.

With regard to labor costs, there are data for each firm on the total value of contractual wages (i.e., value of wages and salaries as specified in labor contracts), the total value of overtime payments, and the total payroll value.[7]

In the study, we follow every establishment in the sample period that provided information on employment for at least two consecutive periods. After imposing some filters that deal with the presence of outliers, which are more likely to be attributed to misreporting,[8] we end up with an unbalanced panel of 657,084 observations, which corresponds to an average of 4,239 establishments for the 155 months in the sample (February 1985 – December 1997).

Figures 1-6 present some descriptive statistics from our sample of establishments. Figure 1 displays the monthly evolution of the average employment level per establishment. Note that Brazilian manufacturing firms increased their average number of workers from about 200 to 280 in the late 1980s, but dramatically reduced it to about 185 in 1997, with most of the reduction occurring between 1990 and 1993, period in which there was a large decrease in import tariffs.

Figure 2 shows the evolution of monthly average hours paid per worker.[9] The two main features of the series are the pronounced constant degree of seasonality and the structural break after the reduction of the standard workweek prescribed by the Constitution of 1988. In fact, average hours decreased from a monthly average of 240 in 1985-1988 to about 225 between 1989 and 1997. Average hours have not fluctuated much over these two periods, with some more variation in 1985-88, reflecting perhaps lower overtime rate costs – the overtime premium was raised in 1988 from 20% to 50% of the regular hourly wage.

Table 1 analyzes this aspect of the Brazilian labor market. It takes the variance of (the log of) total hours across all establishments in the sample in all periods before and after the new Constitution and decomposes it into the variance of (the log of) average hours, the variance of (the log of) employment, and two times the covariance of the two terms (see, for instance, Hansen (1985), and Van Audenrode (1994). The results show that employment variation accounts for 98.9% of total hours variance after the new Constitution and 98.6% before its promulgation. In other words, the Table shows that Brazilian manufacturing firms adjust labor input mostly through employment changes, rather than through average hours worked.[10]

[7]In addition to contractual wages and overtime payments, payroll includes severance payments and other firing penalties, payments related to incentive schemes, fringe benefits, payments due to hazardous activities, paid vacations, night shifts and other compensating schemes. Employers' contributions to social security, training programs and other social programs are not included in the data. These are fixed fractions of the total value of payroll and have remained fairly constant across the sample period, with very few changes.

[8]We only considered firms that reported less than 330 hours per month; positive values for hours, employment, wages and payroll; and that presented no inconsistencies with regard to separation and hiring rates.

[9]Note that this includes hours paid but not worked such as one day of rest per week.

[10]Note that the variance decomposition exercise is performed across establishments and that

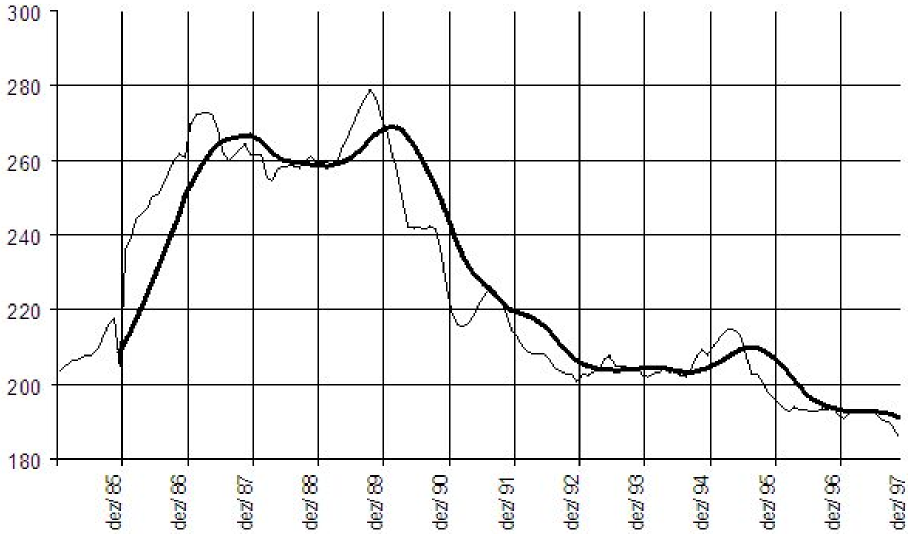

Figure 1
Average employment

Table 1
Variance decomposition of total hours – Monthly data

	Variance of logs			
	Total hours	Average hours	Employment	Cov(logH/N,logN)
Before August 1988	2.735	0.026	2.697	0.012
%	100	1	98.6	0.4
After January 1989	2.928	0.029	2.896	0.002
%	100	1	98.9	0.1

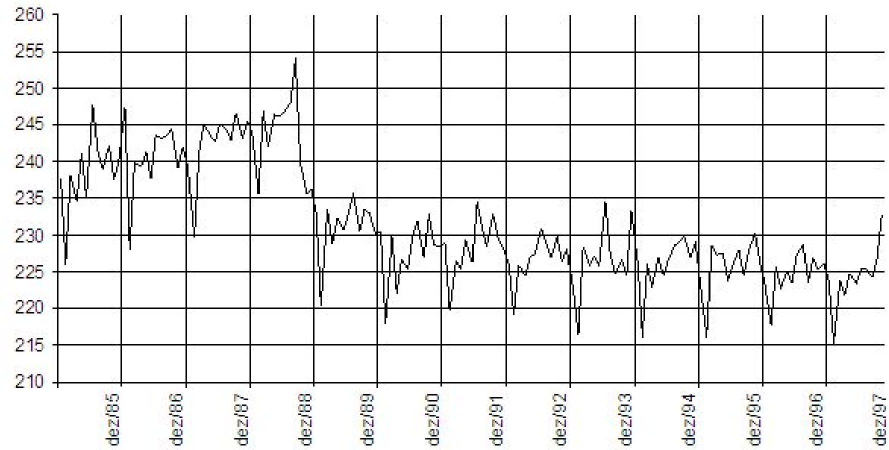

Figure 2
Monthly average hours per worker

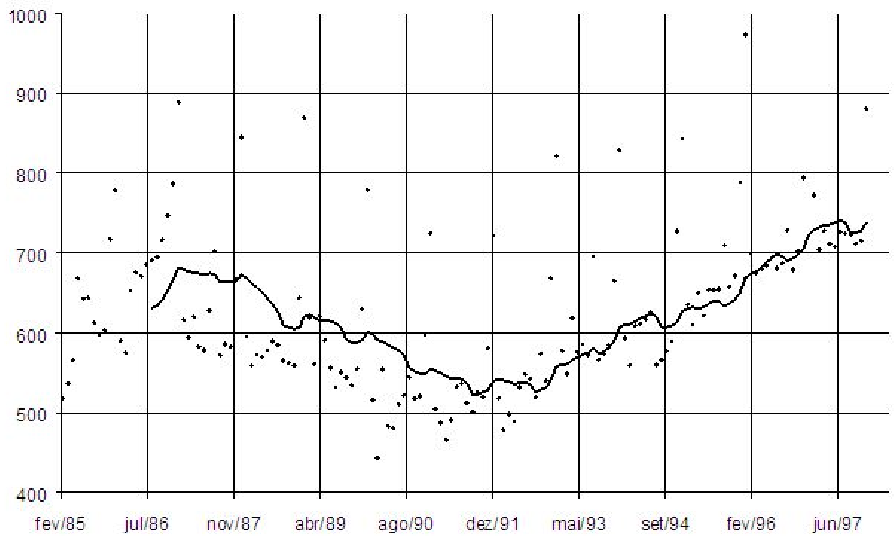

Figure 3
Average payroll per worker

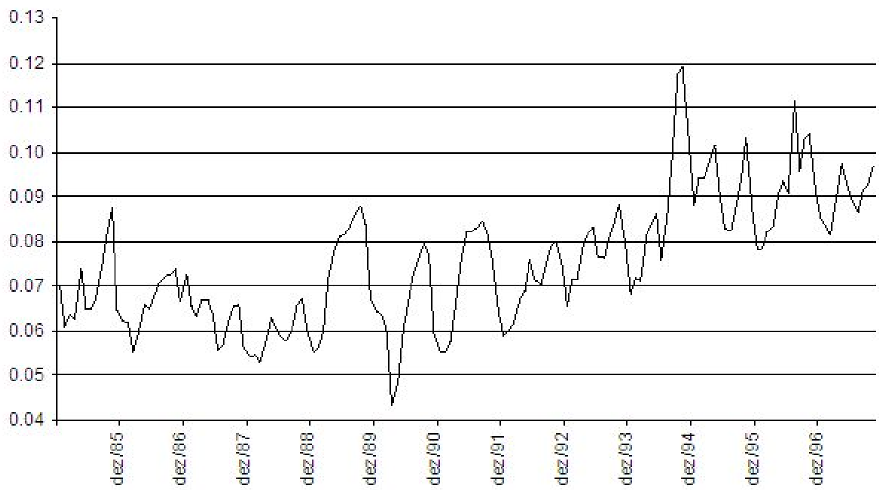

Figure 4
Overtime payments per contractual wage

This suggests that the costs of adjusting hours in Brazil are relatively more expensive than those of adjusting employment for most firms. Overtime costs are relatively high in Brazil (50% higher than regular hourly wages after 1988). There are also significant undertime costs. Although there are no labor code restrictions on firms that want to hire below 44 hours a week, there is jurisprudence in labor courts determining that benefits (13th month wage, vacation, vacation bonus, etc.) should be paid as if workers were hired for the standard working time.[11]

Table 2 investigates the degree of lumpiness in Brazilian firms by presenting the proportions of observations with no employment adjustment in the full sample and by establishment size. The results show that, on average, 27.2% of the establishments do not change the level of employment between two consecutive months. This effect is much higher for small firms, those with size below the median in the sample period: 42.6% of small firms do not change the employment level, compared with 11.4% of the large firms. Since some attrition is more likely to be present in large firms, we also compute the proportion of firms with very small

no time trend is included. Van Audenrode (1994) reports that countries with data on hours paid tend to display less variation in hours than countries with data on hours worked. Nonetheless, the portion attributed to employment variation in Brazil is much larger than that found in other countries, even when compared with that observed in countries with hours-paid-data.

[11]In 1998, a labor law regulated this matter, but it has not been very effective since it requires unions' approval in collective agreements.

negative adjustment, with employment changes between −0.2 and 0.0. Table 2 shows that 17.7% of the firms are in this range, with not much variation according to firm size. As we discussed above, this evidence of lumpiness in employment adjustment at the firm level encourages the use of the CEH methodology.

Table 2
Frequency of employment adjustment (%)

		No employment changes	Employment changes within [−0.02,0]	Number of observations
Total		27.2	17.7	657084
Size				
	above median	11.4	18.8	331096
	below median	42.6	16.3	325988

Figures 3 and 4 describe payroll per worker and overtime per wage payments, respectively, both showing a rising tendency during the 1990s. Figure 5 depicts the two main gross turnover variables available in the data: the hiring rate and the separation rate (number of hires and separations, respectively, divided by average employment in two consecutive periods). The Figure confirms the very high turnover rates observed in Brazil, a stylized fact documented in many other studies. Separation rates of about 6% were observed, on average, during the sample period. Very high but declining hiring rates were also observed. In fact, the decrease in hiring rates from about 5% in the 1980s to about 3% in the 1990s was reflected on an acute decrease of manufacturing employment in Brazil over the last decade.

Figure 6 displays hiring and separation rates by net employment changes (as in Burgess et al., 2001). The Figure shows that:

i) growing firms typically grow by increasing hiring and declining firms typically decrease employment by increasing separations; and

ii) separation rates for growing firms are usually higher than hiring rates for declining firms.

4. Empirical Results

4.1 Estimation of θ_j for each sector

In this subsection, we report the results of the first step of the methodology described in Section 2 – the estimation of equation (2), reproduced below for convenience. As mentioned above, equation (2) was estimated using only changes in hours and employment larger than one standard deviation; in its normal and

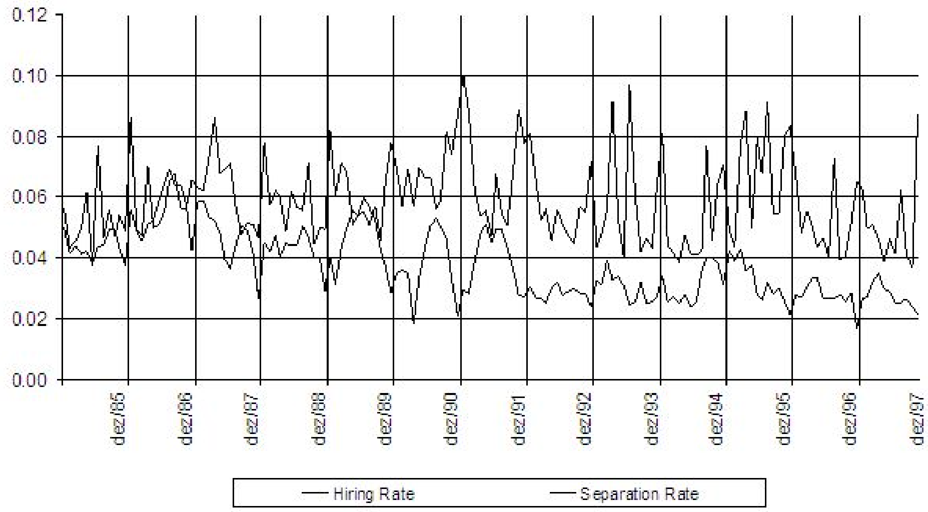

Figure 5
Hiring and separation rates

reverse order; and for the pre and post 1988 Constitution periods. The results for each of the 22 manufacturing sectors are displayed in Table 3. The column "convex combination" refers to the optimal convex combination of the estimated coefficients in the normal and reverse order equations. Standard errors are shown in parentheses.

$$\triangle e_{it} = -\theta_j \triangle h_{it} + \triangle e^*_{it} = -\theta_j \triangle h_{it} + \varepsilon_{it} \tag{4}$$

Note that, as expected, the results are different for before and after the new Constitution. All coefficients are significantly different from zero. Estimates of the convex combination of θ vary from 0.21 to 0.82, averaging 0.52 in the pre Constitution period, and from 0.34 to 0.74, averaging 0.50 in the post Constitution period. The next subsection calculates employment adjustment functions and interprets the results.

4.2 Employment adjustment functions

As described above, the second step of the methodology is to compute employment deviations (gaps) and the employment adjustment function using the estimates of θ for each sector. In this subsection, we present the main results for all establishments in the sample.

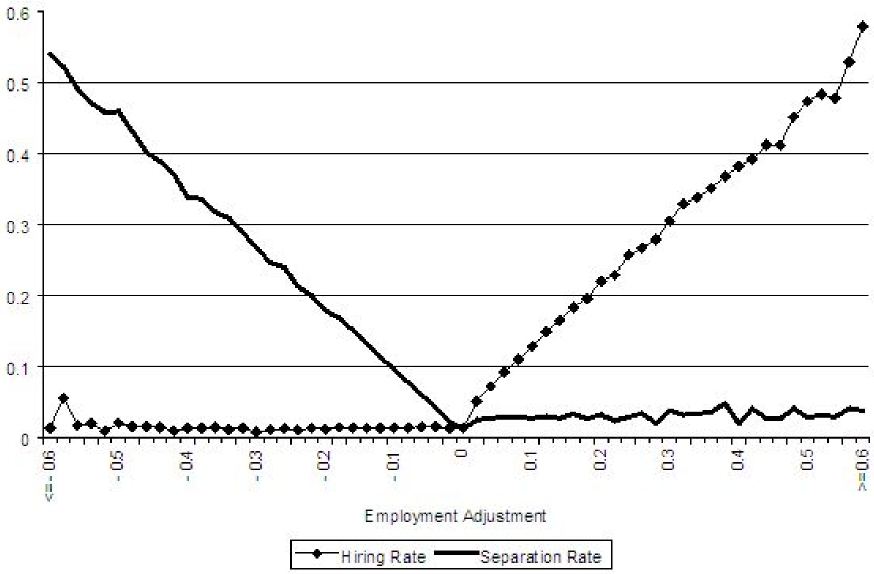

Figure 6
Hiring and Separation Rates according to Employment Adjustment

Table 3
Estimates of θ

Monthly data, observations above one standard deviation

A. Before the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	1.177	0.171	0.488	0.071	0.589
Perfumes	0.832	0.054	0.575	0.038	0.658
Machinery and equipment	0.648	0.065	0.539	0.054	0.584
Paper	0.308	0.082	0.182	0.048	0.214
Electrical material	0.674	0.077	0.529	0.060	0.584
Leather	0.641	0.079	0.468	0.057	0.528
Transportation material	0.611	0.067	0.524	0.057	0.561
Plastic	0.838	0.115	0.285	0.039	0.342
Wood	0.564	0.078	0.402	0.055	0.457
Non-metallic minerals	0.557	0.071	0.576	0.074	0.566
Clothing	0.548	0.095	0.595	0.103	0.570
Others	0.454	0.080	0.326	0.057	0.369
Chemicals	0.661	0.122	0.356	0.066	0.424
Printing	0.986	0.101	0.565	0.058	0.669
Pharmaceuticals	0.711	0.078	0.477	0.052	0.550
Furniture	0.409	0.131	0.182	0.058	0.219
Metallurgy	0.887	0.078	0.530	0.047	0.624
Beverages	0.792	0.050	0.546	0.035	0.626
Food	0.510	0.093	0.558	0.102	0.532
Textile	1.073	0.122	0.710	0.081	0.821
Mineral extraction	0.762	0.065	0.504	0.043	0.582
Tobacco	0.548	0.083	0.444	0.067	0.485
B. After the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.578	0.092	0.313	0.050	0.373
Perfumes	0.662	0.053	0.336	0.027	0.403
Machinery and Equipment	0.663	0.057	0.346	0.030	0.414
Paper	0.814	0.038	0.644	0.030	0.709
Electrical Material	0.652	0.052	0.449	0.036	0.514
Leather	0.450	0.048	0.359	0.039	0.395
Transportation Material	0.668	0.044	0.557	0.036	0.602
Plastic	0.828	0.050	0.486	0.029	0.574
Wood	0.655	0.059	0.476	0.043	0.538
Non-metallic minerals	0.774	0.079	0.355	0.036	0.428
Clothing	0.571	0.070	0.396	0.049	0.453
Others	0.711	0.051	0.344	0.025	0.414
Chemicals	0.599	0.095	0.294	0.047	0.353
Printing	0.780	0.069	0.462	0.041	0.545
Pharmaceuticals	0.493	0.051	0.404	0.042	0.440
Furniture	0.810	0.070	0.319	0.028	0.385
Metallurgy	0.616	0.039	0.679	0.043	0.645
Beverages	0.778	0.034	0.564	0.024	0.637
Food	0.611	0.072	0.282	0.033	0.340
Textile	1.166	0.087	0.620	0.046	0.741
Mineral extraction	0.704	0.040	0.587	0.033	0.635
Tobacco	0.591	0.045	0.507	0.039	0.542

Obs: θ is the coefficient of hours changes in the regression of employment changes on hours changes, using only observations above one standard deviation. All regressions include firm-fixed effects.

Figure 7 shows the average monthly employment adjustment function and the distribution of employment deviations. To facilitate the exposition we only show in the figure the lines of employment deviation corresponding to the grids between −1.0 and 1.0. As in CEH, a cubic spline is used to smooth the employment adjustment function and is also shown in the graph.

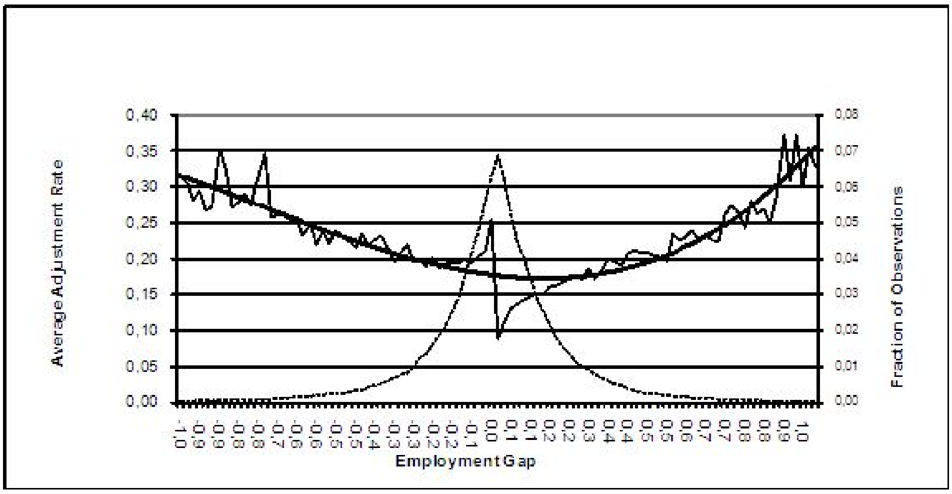

Figure 7
Employment adjustment function and employment gap distribution – Monthly data, convex combination of θ

The figure shows that the employment deviation distribution has a peak at zero, with most of the observations ranging from −0.3 to 0.3. The employment adjustment function seems to be symmetric around the origin, but it increases with the size of the employment gap. This contradicts the quadratic adjustment cost model and is compatible with the linear fixed costs of the adjustment model, as expected, given the lumpiness in the data revealed by Table 2. Note that, on average, between around 10 to 20% of the employment gap is closed for small employment deviations (less than 10%), while for employment deviations larger than 30% in absolute value, employment adjustments fluctuate between 20 and 35%.

This result reveals a lot of inaction in the monthly data, with very small employment adjustment at the firm level. The use of more frequent data, on a monthly basis, deserves further examination. On the one hand, one could question whether firms take decisions regarding the optimal employment level at that high frequency. Moreover, there is probably more noise in monthly data than at lower frequencies. On the other hand, the use of quarterly data may "bias the results toward inferring that factor demand adjusts smoothly" (Hamermesh and Pfann, 1996).

One of the advantages of monthly data is that one can easily transform the data into a quarterly frequency and study what the differences in the results would be if one only had access to quarterly data. In order to accomplish this task we use the employment level observed in the second month of each quarter and the sum of the total number of hours worked in each quarter. Table A.1 in the Appendix shows the estimates of θ at a quarterly frequency. Note that the estimated coefficients are somewhat smaller, concentrated around 0.3.

With these estimated coefficients, we compute employment deviations and the employment adjustment function at a quarterly frequency. Figure 8 presents the results. Note that the values of employment adjustment function are much closer to one (around 0.7 for employment gaps larger than 30% in absolute value) than in the monthly data. For smaller employment deviations (less than 10%), the employment adjustment rates range from 0.5 to 0.6. This is similar to the quarterly employment adjustment functions estimated with U.S. data reported in CEH. Also note that values of employment gap close to zero are much less frequent than in the case of monthly data.

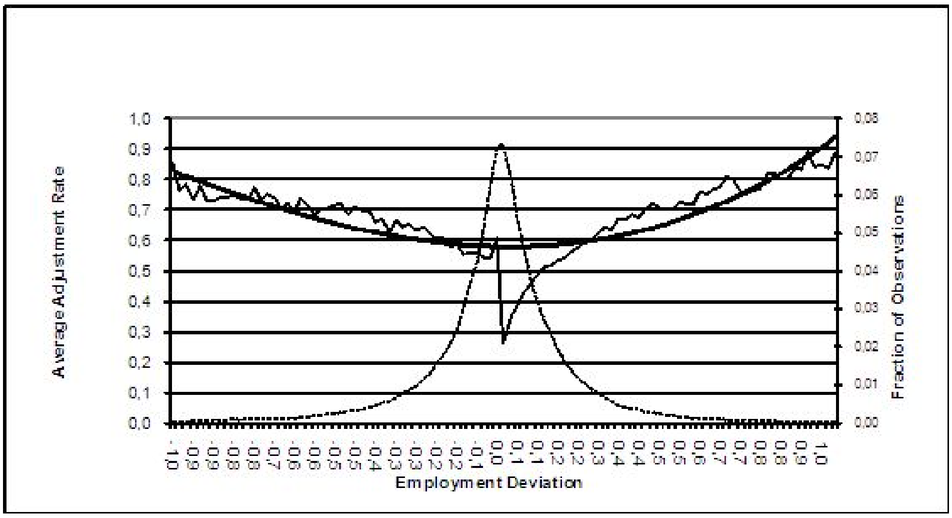

Figure 8
Employment adjustment function and employment gap distribution – Quarterly data

The results suggest that there is a substantial gain in using monthly data. The picture that emerges from the use of quarterly data is one with much more employment adjustment even for relatively small employment gaps. This contrasts with the results for monthly data that show more inaction, especially for small employment deviations. Note that the form of employment adjustment functions in both cases is compatible with linear or fixed employment adjustment costs, but the functions increase in a more pronounced way when monthly data are used. Nonetheless, care should be taken when interpreting the results given the discussion above about the adequacy of the methodology for firms that do not resort to hours adjustment when hit by a shock to the desired employment.[12]

4.3 Robustness analysis

As discussed in subsection 2.2, we perform a robustness analysis in order to study how sensitive the main results are to alternative ways of dealing with both the measurement error and the endogeneity of hours changes. First, with regard to the measurement error, we argued that the choice of using the convex combination of the estimations θ from the normal and reverse order regressions was arbitrary. In Figures 9 and 10, we present the estimates of monthly employment adjustment functions and employment gaps using, respectively, the upper and lower bounds of θ, from the normal and reverse order regressions presented in Table 3 – note that the regression coefficient is *minus* θ.

As expected, when larger values of θ are used, as in Figure 9, one gets lower values of the employment adjustment function, which increase from 10% for small employment gaps to 20% for large ones. When the lower bound of θ is used, as in Figure 10, the opposite occurs, with larger values of the employment adjustment function, which ranges from 20% for small employment gaps to 35% for large ones. Nonetheless, both Figures show employment adjustment functions that increase with the level of employment gaps, which is consistent with non-convex employment adjustment costs.

Second, as discussed in subsection 2.2, in order to deal with the bias in the estimation of θ coming from a possible correlation between variations in hours and employment, when changes are small, we also estimated equation (2) using more stringent filters (above two standard deviations) and more flexible filters (above half a standard deviation and using all observations). Tables A.2 to A.4 display the estimates of θ obtained through the use of these alternative filters of the observations of hours and employment changes. As expected, given the direction of the bias, we got larger estimates of θ when a more strict filter is used and smaller estimates of θ when more flexible filters are used. The estimated coefficients in Table A.2 average 0.66 for the Pre-Constitution period and 0.61 for the Post-Constitution period. The averages of the estimated θ's when the more flexible filters are used, are respectively 0.42 and 0.41, when using half a standard deviation (Table A.3); and 0.21 and 0.23 when using all observations (Table A.4).

Figures 11 to 13 display estimates of monthly employment adjustment functions and employment gaps using these three sets of alternative estimates of θ. A pattern

[12] Results (not shown here) for seasonally adjusted data are very similar.

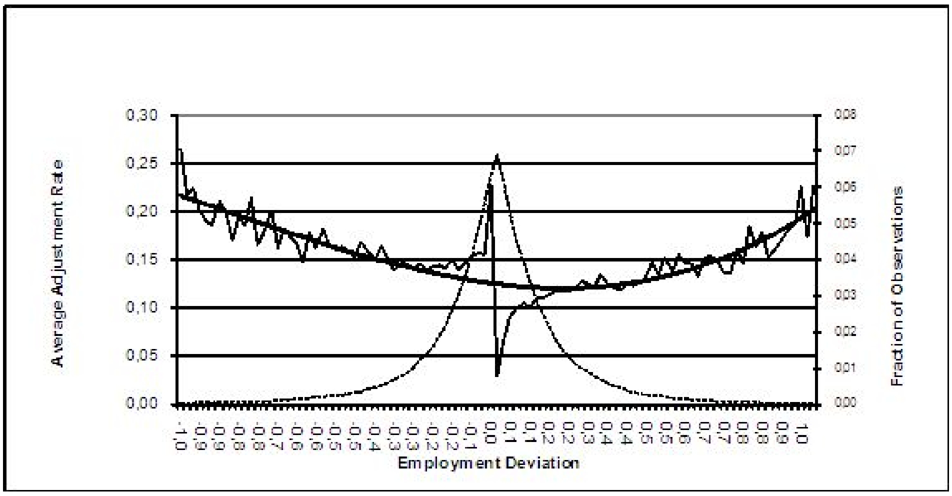

Figure 9
Employment adjustment function and employment gap distribution – Monthly data, upper bound of θ

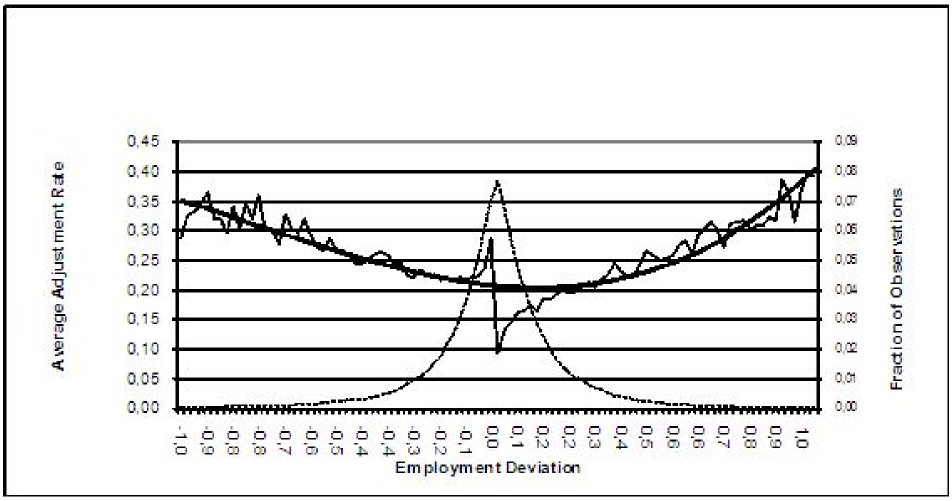

Figure 10
Employment adjustment function and employment gap distribution – Monthly data, lower bound of θ

similar to that observed in Figures 8 and 9 emerges. In Figure 11, when larger estimated θ's are used, lower employment adjustment rates are found, ranging from 15 to 25%. Figure 12 is an intermediate case, with adjustment rates ranging from 20 to 45%. When we use all observations to estimate a possibly biased θ, as in Figure 13, adjustment rates range from 40 to 80%. Again, in all cases, the employment adjustment functions are increasing in the values of the employment gaps.

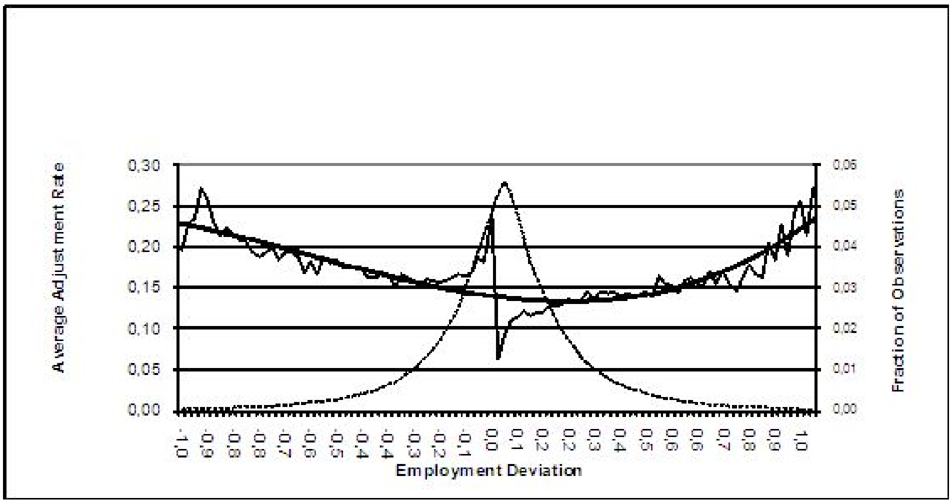

Figure 11
Employment adjustment function and employment gap distribution – Monthly data, observations greater than 2 std dev

4.4 Employment adjustment according to firm characteristics

In this subsection, we analyze how the employment adjustment function varies according to several establishment characteristics, such as skilled-labor intensity, size, payroll expenses, and overtime payments.

One should expect that establishments that have characteristics associated with lower employment adjustment costs should display higher employment adjustment rates for each employment deviation level, i.e. firms with lower adjustment costs should fill a larger portion of each level of employment gap. For most characteristics, we divide the establishments into two groups: a group with levels of that characteristic above the median and the other group with levels below the median. The analysis is based on plots of the employment adjustment functions for the two groups (Figures 14-17) and on econometric tests of mean equality across employment deviation levels (Table 4).

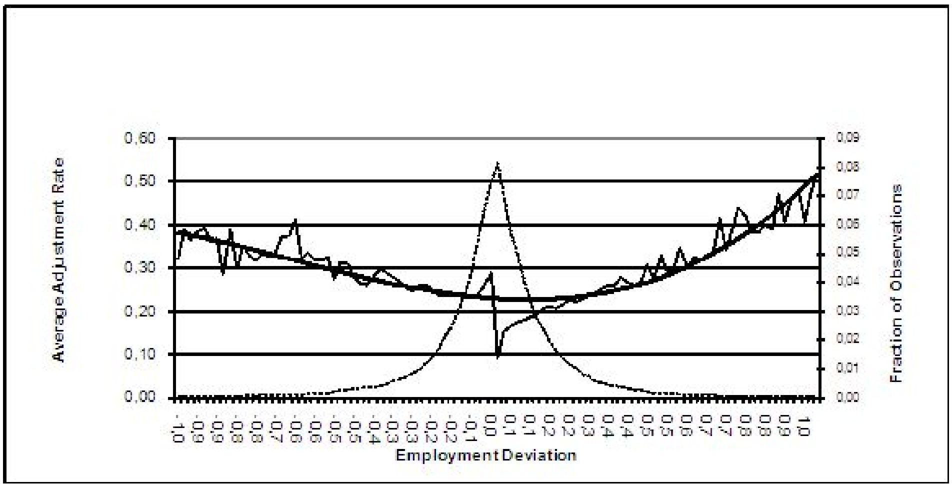

Figure 12
Employment adjustment function and employment gap distribution – Monthly data, observations greater than 1/2 std dev

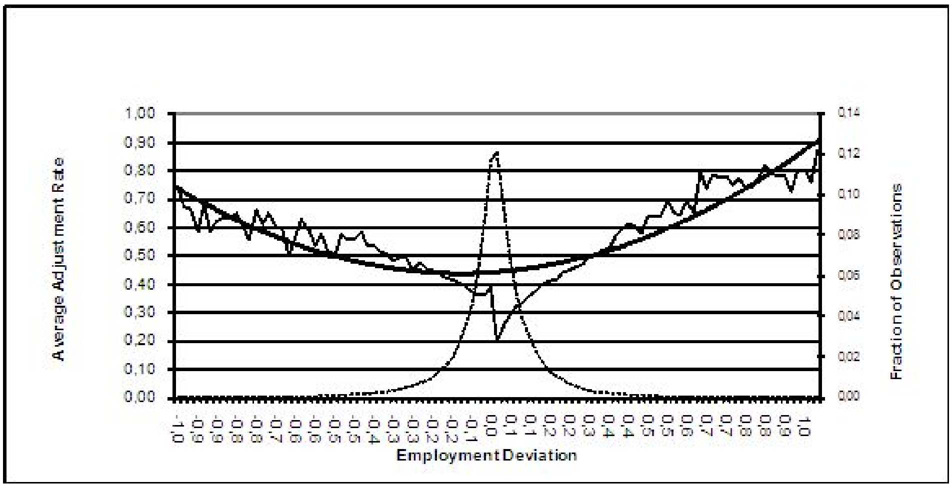

Figure 13
Employment adjustment function and employment gap distribution – Monthly data, all observations

Table 4
Mean-difference tests of employment adjustment rates by firm characteristics

		Mean	P-value	Number of observations
Skill	6 high-skill	0.964	0.023	142
	6 low-skill	0.982		
Size	above median	0.932	0.001	149
	below median	0.975		
Payroll/Contractual wage	above median	0.962	0.221	151
	below median	0.948		
Overtime per wage payments	above median	0.962	0.074	150
	below median	0.974		

In Figure 14, we compare the average employment adjustment function for the six less skill-intensive sectors with that for the six most skill-intensive sectors, based on the proportion of workers with more than 11 years of schooling in each sector.[13] One should expect lower employment adjustment costs in low-skill sectors and, therefore, more employment adjustment for a given labor shortage in these sectors. Figure 14 confirms this prior.

Figure 15 disaggregates the adjustment function according to establishment size. It shows a very different behavior for large and small firms. Large firms tend to adjust less to the same employment gap levels, especially for negative ones. This is also expected since large firms tend to have higher employment adjustment costs.

Figure 16 depicts employment adjustment functions by payroll/contractual wage payment ratios, which is a measure of benefit payments and compliance with the labor legislation. The idea is that firms with higher payroll/wage benefits face a more organized labor force and therefore higher employment adjustment costs. On the other hand, since severance payments are included in payroll expenditures, firms that are firing too much could end up with high payroll/wage ratios. The Figure shows that firms with payroll/wage ratios above the median hire less quickly and fire more quickly than firms below the median.

Figure 17 disaggregates the employment adjustment function by overtime/contractual wage payments. Note that this measure is related to a component of the proxy for the employment deviation itself, the distance of current hours from time averages, although it is measuring only one aspect of it. The intention of this exercise is, therefore, to complement the evidence. The prior is that firms that

[13] Proportions of skilled workers are based on data from PNAD (*Brazilian National Household Survey*). The low-skill sectors are wood, leather, non-metallic minerals, clothing, furniture, and coffee; the high-skill sectors are chemicals, tobacco, drugs, printing, electrical material, and machinery and equipment.

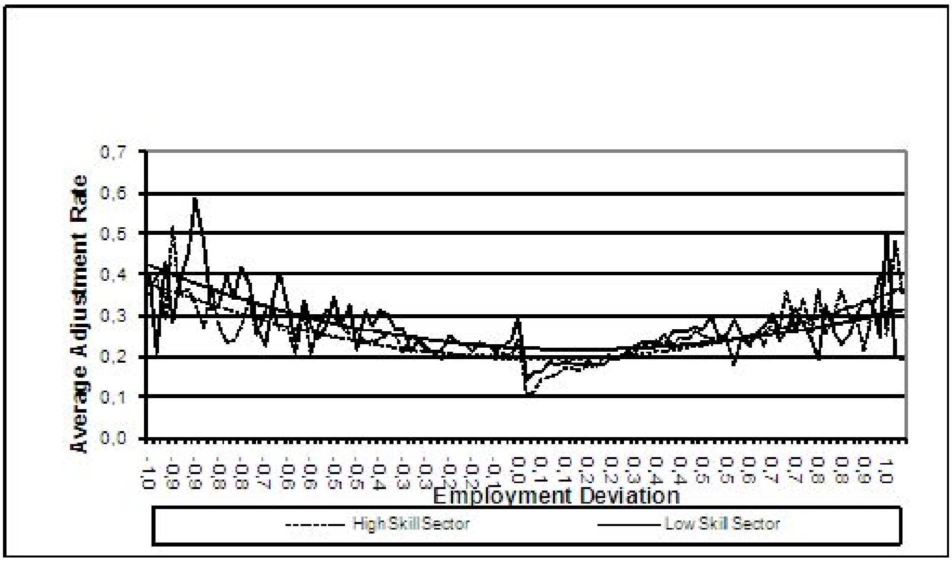

Figure 14
Employment adjustment function and employment gap distribution – Monthly data, by skilled-labor intensity

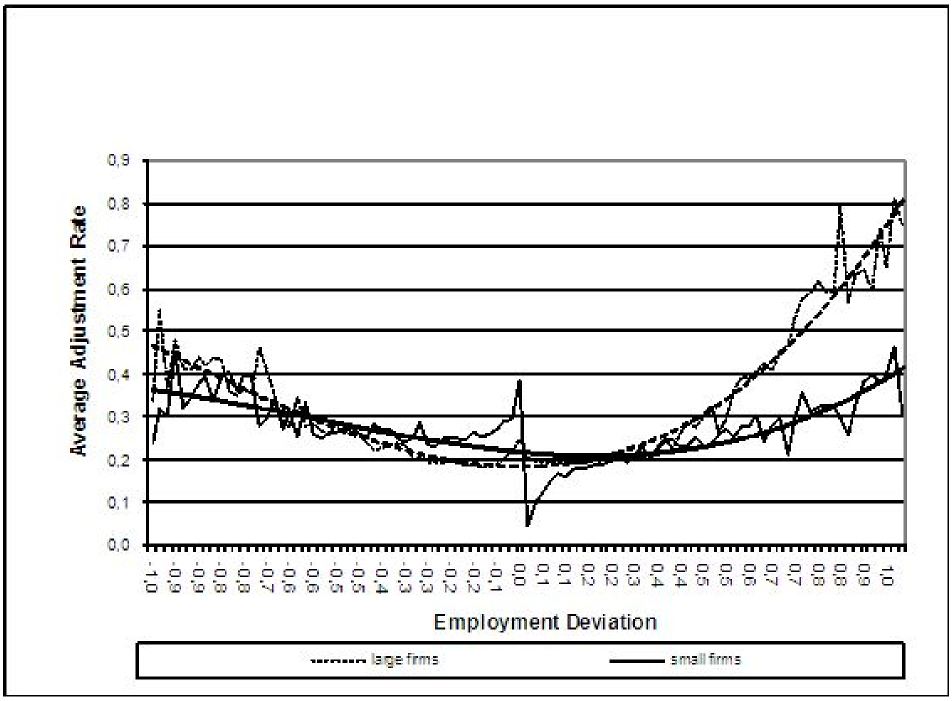

Figure 15
Employment adjustment function and employment gap distribution – Monthly data, by establishment size

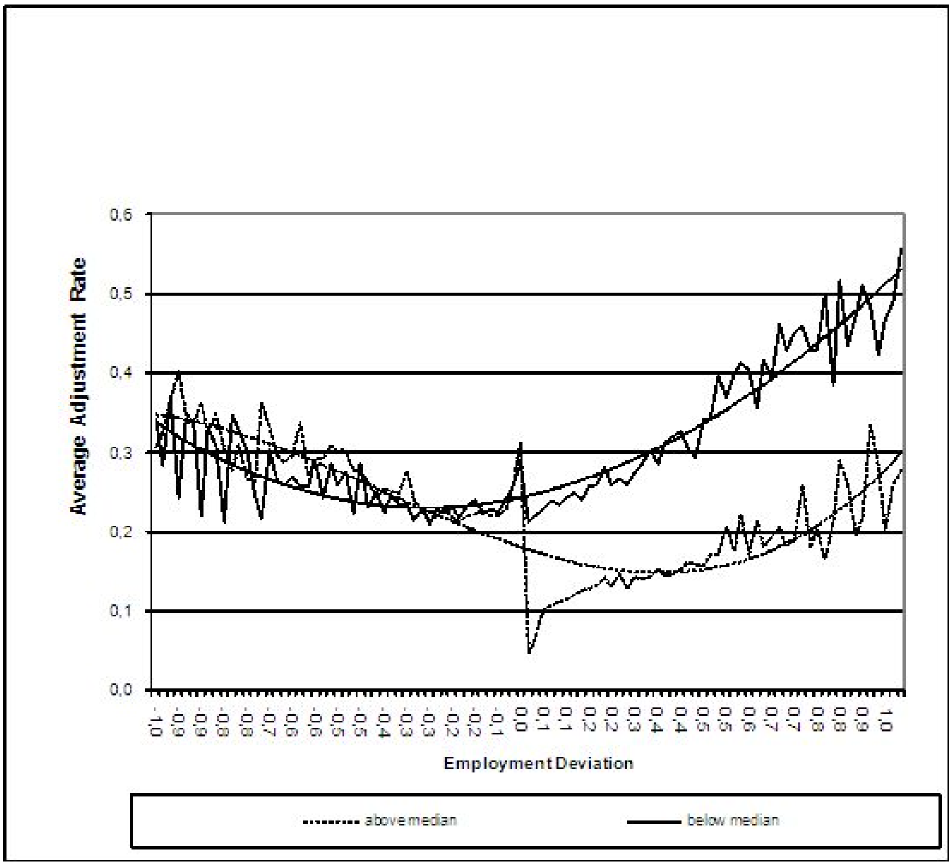

Figure 16
Employment adjustment function and employment gap distribution – Monthly data, by payroll per wage

are spending more on overtime are probably varying their level of employment less for a given employment gap. Figure 17 confirms this prior by showing a higher adjustment function for firms with overtime payment ratios below the median.

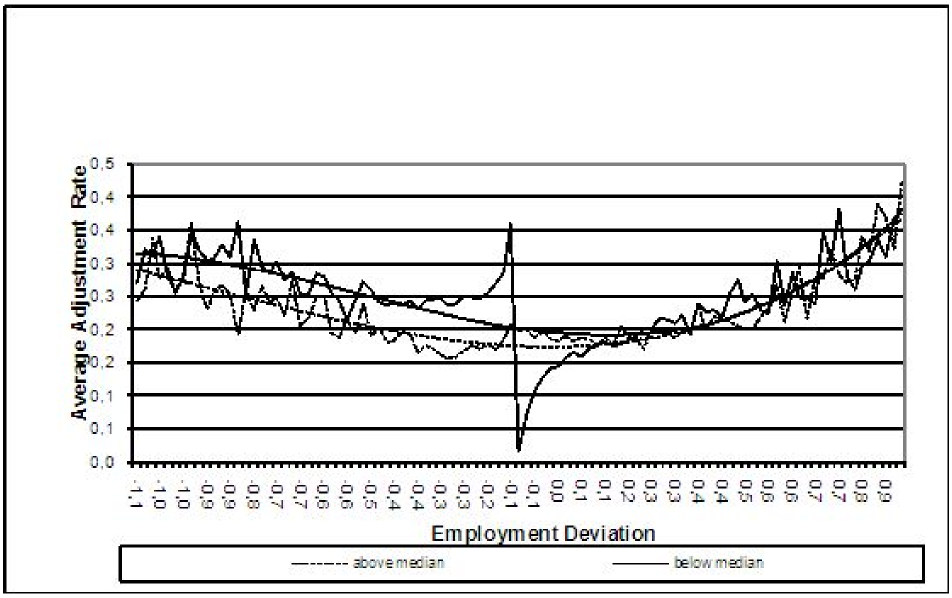

Figure 17
Employment adjustment function and employment gap distribution – Monthly data, by overtime payments per wage

Table 4 presents the means of the employment adjustment functions across employment deviation grids for each of the two groups of establishments and each characteristic analyzed above. The table also presents the p-values of testing the null hypothesis that the means of each two groups (high and low) are the same. The results confirm the visual impression from Figures 14-17. One rejects that the means of the two groups (high and low) are the same at reasonable significance values for each characteristic with the exception of payroll/contractual wage payment ratios.

The results of this subsection suggest that there is a variation in the degree of lumpiness across firms. The employment adjustment function tends to have a higher mean and to display larger values for small employment deviations when measured for establishments with characteristics that are arguably related to lower costs of employment adjustment: larger proportion of low-skilled workers, smaller size and lower overtime payments.

5. Conclusions

In this paper, we investigated the dynamics of labor adjustment at the firm level in Brazilian manufacturing, using information on average hours per worker to measure employment deviation from desired levels as in CEH (1997).

The objective of the study was to estimate the employment adjustment function, which relates the magnitude of employment changes to the size of employment gaps, the distance between observed and desired employment levels. We initially reported a substantial amount of inaction in employment adjustment in the monthly data. On average, 27.2% of the establishments do not change the level of employment between two consecutive months. This effect is much higher for small firms, with 42.6% of them not adjusting employment.

The estimates of employment adjustment functions are compatible with the presence of nonconvexities in employment adjustment costs in Brazilian manufacturing, with estimated employment adjustment rates increasing with the size of employment gaps. On average, employment adjustment rates range from 10% for small employment gaps to 35% for large ones. These numbers are lower than those obtained when we aggregate the Brazilian data to the quarterly frequency, which are more in line with the results found for other countries (for example, the CEH study for the U.S.).

We ran several robustness tests with alternative ways of estimating the employment gaps, using other forms of dealing with measurement error and a problem of endogeneity of the hours change variable. Although the magnitudes of employment adjustment rates vary, we show that:

i) the variations are in line with the expected directions of the biases in estimating the coefficient of the hours change variable; and

ii) the format of employment adjustment functions does not change across specifications, always revealing that employment adjustment rates increase with the size of employment gaps, which is compatible with non-convex costs of employment adjustment.

Finally, we studied how the employment adjustment function varies according to several establishment characteristics, such as skilled-labor intensity, size, payroll expenses, and overtime payments. The results suggest that there is variation in the degree of lumpiness across firms. The employment adjustment function tends to have a higher mean and to display larger values when measured for establishments with characteristics that are arguably related to lower costs of employment adjustment: larger proportion of low-skilled workers, smaller size and lower overtime payments.

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Table A.1: Estimates of θ

Quarterly data, observations above one standard deviation

A. Before the Constitution of 1988

	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	1.147	0.419	0.256	0.094	0.299
Perfumes	1.203	0.171	0.296	0.042	0.347
Machinery and equipment	1.347	0.146	0.383	0.041	0.456
Paper	1.446	0.188	0.290	0.038	0.335
Electrical material	1.390	0.208	0.319	0.048	0.373
Leather	0.750	0.217	0.208	0.060	0.246
Transportation material	0.160	0.161	0.131	0.132	0.143
Plastic	1.833	0.200	0.345	0.038	0.395
Wood	1.326	0.171	0.404	0.052	0.482
Non-metallic minerals	1.163	0.174	0.521	0.078	0.628
Clothing	1.411	0.352	0.316	0.079	0.368
Others	2.356	0.332	0.192	0.027	0.206
Chemicals	1.681	0.232	0.314	0.043	0.360
Printing	1.983	0.223	0.355	0.040	0.406
Pharmaceuticals	1.627	0.172	0.384	0.040	0.450
Furniture	1.754	0.578	0.163	0.054	0.177
Metallurgy	1.366	0.272	0.174	0.035	0.193
Beverages	2.021	0.210	0.228	0.024	0.251
Food	1.440	0.189	0.363	0.048	0.427
Textile	3.477	2.807	0.052	0.042	0.052
Mineral extraction	1.148	0.139	0.368	0.045	0.441
Tobacco	1.294	0.199	0.388	0.060	0.462

B. After the Constitution of 1988

	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	1.223	0.228	0.207	0.039	0.236
Perfumes	1.636	0.128	0.250	0.020	0.282
Machinery and equipment	1.137	0.119	0.270	0.028	0.316
Paper	1.130	0.132	0.222	0.026	0.255
Electrical material	1.105	0.135	0.288	0.035	0.340
Leather	1.007	0.120	0.241	0.029	0.282
Transportation material	1.049	0.174	0.191	0.032	0.218
Plastic	1.635	0.132	0.263	0.021	0.298
Wood	0.558	0.095	0.494	0.084	0.522
Non-metallic minerals	1.418	0.124	0.350	0.031	0.411
Clothing	1.193	0.189	0.221	0.035	0.253
Others	1.638	0.159	0.203	0.020	0.224
Chemicals	1.421	0.128	0.394	0.035	0.467
Printing	1.437	0.171	0.263	0.031	0.301
Pharmaceuticals	1.054	0.127	0.295	0.036	0.350
Furniture	1.093	0.201	0.193	0.035	0.220
Metallurgy	0.630	0.146	0.126	0.029	0.146
Beverages	1.008	0.142	0.136	0.019	0.152
Food	1.879	0.162	0.253	0.022	0.281
Textile	4.443	0.557	0.150	0.019	0.155
Mineral extraction	1.596	0.124	0.268	0.021	0.305
Tobacco	1.397	0.107	0.318	0.024	0.371

Obs: θ is the coefficient of hours changes in the regression of employment changes on hours changes, using only observations above one standard deviation. All regressions include firm-fixed effects.

Table A.2: Estimates of θ

Monthly data, observations above two standard deviation

A. Before the Constitution of 1988

	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	1.414	0.290	0.513	0.105	0.618
Perfumes	1.061	0.076	0.745	0.054	0.850
Machinery and equipment	0.706	0.173	0.645	0.158	0.672
Paper	0.278	0.189	0.198	0.135	0.225
Electrical material	0.814	0.151	0.744	0.138	0.776
Leather	1.022	0.212	0.579	0.120	0.687
Transportation material	0.975	0.148	0.631	0.096	0.733
Plastic	1.327	0.366	0.318	0.088	0.373
Wood	0.595	0.207	0.571	0.199	0.583
Non-metallic minerals	0.816	0.109	0.856	0.115	0.835
Clothing	0.454	0.137	1.614	0.487	0.539
Others	0.613	0.154	0.508	0.128	0.551
Chemicals	0.730	0.429	0.400	0.235	0.477
Printing	1.326	0.289	0.511	0.111	0.616
Pharmaceuticals	1.043	0.157	0.727	0.110	0.830
Furniture	0.863	0.246	0.283	0.081	0.339
Metallurgy	1.101	0.051	0.885	0.041	0.970
Beverages	0.878	0.071	0.676	0.055	0.752
Food	0.512	0.216	0.625	0.263	0.557
Textile	1.094	0.262	0.626	0.150	0.741
Mineral extraction	0.977	0.120	0.728	0.089	0.817
Tobacco	1.034	0.123	0.869	0.104	0.937

B. After the Constitution of 1988

	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.556	0.115	0.626	0.129	0.587
Perfumes	0.672	0.111	0.403	0.067	0.474
Machinery and equipment	0.790	0.156	0.311	0.061	0.375
Paper	0.910	0.060	0.878	0.058	0.893
Electrical material	0.774	0.110	0.626	0.089	0.685
Leather	0.373	0.101	0.381	0.103	0.377
Transportation material	0.712	0.064	0.854	0.077	0.770
Plastic	0.843	0.098	0.671	0.078	0.738
Wood	0.914	0.071	0.863	0.067	0.887
Non-metallic minerals	0.671	0.235	0.264	0.092	0.318
Clothing	0.547	0.166	0.397	0.121	0.448
Others	0.943	0.080	0.516	0.044	0.615
Chemicals	0.559	0.261	0.308	0.144	0.366
Printing	1.045	0.170	0.478	0.078	0.576
Pharmaceuticals	0.698	0.114	0.660	0.108	0.678
Furniture	0.929	0.125	0.382	0.052	0.462
Metallurgy	0.615	0.068	0.864	0.095	0.699
Beverages	0.884	0.049	0.679	0.038	0.755
Food	0.813	0.181	0.292	0.065	0.352
Textile	1.025	0.107	0.787	0.082	0.875
Mineral extraction	0.789	0.053	0.893	0.060	0.835
Tobacco	0.658	0.087	0.624	0.083	0.640

Obs: θ is the coefficient of hours changes in the regression of employment changes on hours changes, using only observations above one standard deviation. All regressions include firm-fixed effects.

Table A.3: Estimates of θ

Monthly data, observations above 1/2 standard deviation

A. Before the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.727	0.088	0.417	0.051	0.494
Perfumes	0.639	0.033	0.424	0.022	0.489
Machinery and equipment	0.411	0.034	0.338	0.028	0.367
Paper	0.254	0.036	0.192	0.027	0.214
Electrical material	0.538	0.040	0.414	0.031	0.460
Leather	0.420	0.036	0.354	0.030	0.381
Transportation material	0.397	0.036	0.370	0.034	0.383
Plastic	0.577	0.057	0.220	0.022	0.266
Wood	0.350	0.035	0.347	0.035	0.348
Non-metallic minerals	0.452	0.044	0.395	0.039	0.420
Clothing	0.577	0.042	0.571	0.042	0.574
Others	0.371	0.045	0.242	0.029	0.280
Chemicals	0.458	0.062	0.251	0.034	0.299
Printing	0.536	0.051	0.476	0.045	0.503
Pharmaceuticals	0.428	0.034	0.390	0.031	0.407
Furniture	0.356	0.065	0.162	0.030	0.195
Metallurgy	0.731	0.041	0.440	0.025	0.518
Beverages	0.684	0.032	0.470	0.022	0.539
Food	0.450	0.044	0.454	0.045	0.452
Textile	1.042	0.093	0.641	0.057	0.751
Mineral extraction	0.674	0.043	0.422	0.027	0.493
Tobacco	0.399	0.040	0.330	0.033	0.358
B. After the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.561	0.059	0.261	0.027	0.314
Perfumes	0.585	0.030	0.284	0.014	0.341
Machinery and equipment	0.505	0.027	0.310	0.017	0.364
Paper	0.670	0.021	0.548	0.017	0.597
Electrical material	0.475	0.030	0.315	0.020	0.364
Leather	0.381	0.027	0.277	0.019	0.313
Transportation material	0.615	0.027	0.420	0.019	0.482
Plastic	0.713	0.031	0.355	0.015	0.427
Wood	0.560	0.029	0.445	0.023	0.490
Non-metallic minerals	0.620	0.038	0.319	0.020	0.382
Clothing	0.462	0.040	0.304	0.026	0.351
Others	0.590	0.032	0.273	0.015	0.328
Chemicals	0.542	0.049	0.274	0.025	0.329
Printing	0.637	0.039	0.396	0.024	0.464
Pharmaceuticals	0.371	0.027	0.292	0.021	0.322
Furniture	0.650	0.040	0.277	0.017	0.334
Metallurgy	0.549	0.023	0.498	0.021	0.521
Beverages	0.703	0.022	0.471	0.015	0.543
Food	0.464	0.037	0.262	0.021	0.311
Textile	1.121	0.075	0.540	0.036	0.650
Mineral extraction	0.609	0.026	0.441	0.019	0.499
Tobacco	0.480	0.028	0.358	0.021	0.401

Obs: θ is the coefficient of hours changes in the regression of employment changes on hours changes, using only observations above one standard deviation. All regressions include firm-fixed effects.

Table A.4: Estimates of θ

Monthly data, all observations

A. Before the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.302	0.020	0.153	0.010	0.184
Perfumes	0.288	0.010	0.233	0.008	0.255
Machinery and equipment	0.185	0.009	0.202	0.010	0.193
Paper	0.114	0.009	0.132	0.010	0.121
Electrical material	0.215	0.010	0.248	0.012	0.229
Leather	0.144	0.009	0.177	0.011	0.157
Transportation material	0.187	0.013	0.158	0.011	0.170
Plastic	0.256	0.016	0.130	0.008	0.155
Wood	0.133	0.011	0.191	0.015	0.152
Non-metallic minerals	0.213	0.016	0.166	0.012	0.184
Clothing	0.350	0.016	0.335	0.015	0.342
Others	0.165	0.010	0.120	0.007	0.136
Chemicals	0.170	0.018	0.115	0.012	0.132
Printing	0.227	0.015	0.234	0.016	0.230
Pharmaceuticals	0.196	0.012	0.199	0.012	0.198
Furniture	0.193	0.013	0.127	0.009	0.147
Metallurgy	0.388	0.012	0.246	0.007	0.287
Beverages	0.450	0.008	0.313	0.006	0.358
Food	0.282	0.014	0.281	0.014	0.281
Textile	0.512	0.032	0.299	0.019	0.353
Mineral extraction	0.288	0.013	0.188	0.009	0.218
Tobacco	0.128	0.012	0.125	0.012	0.126
B. After the Constitution of 1988					
	Normal Order		Reverse order		Convex
Sector	θ	Std error	θ	Std error	Combination
Rubber	0.191	0.010	0.168	0.008	0.178
Perfumes	0.239	0.008	0.138	0.004	0.164
Machinery and equipment	0.210	0.006	0.224	0.006	0.216
Paper	0.290	0.006	0.340	0.007	0.311
Electrical material	0.172	0.008	0.152	0.007	0.161
Leather	0.160	0.007	0.155	0.007	0.158
Transportation material	0.276	0.008	0.205	0.006	0.230
Plastic	0.339	0.009	0.198	0.005	0.234
Wood	0.245	0.007	0.299	0.009	0.267
Non-metallic minerals	0.303	0.011	0.199	0.007	0.231
Clothing	0.248	0.012	0.197	0.009	0.217
Others	0.263	0.007	0.186	0.005	0.211
Chemicals	0.297	0.011	0.200	0.008	0.231
Printing	0.287	0.011	0.254	0.009	0.268
Pharmaceuticals	0.166	0.008	0.161	0.008	0.163
Furniture	0.286	0.009	0.175	0.005	0.205
Metallurgy	0.278	0.006	0.258	0.006	0.267
Beverages	0.432	0.005	0.338	0.004	0.374
Food	0.213	0.010	0.158	0.008	0.178
Textile	0.645	0.026	0.281	0.011	0.339
Mineral extraction	0.269	0.008	0.208	0.006	0.231
Tobacco	0.226	0.008	0.195	0.007	0.208

Obs: θ is the coefficient of hours changes in the regression of employment changes on hours changes, using only observations above one standard deviation. All regressions include firm-fixed effects.