Essays on the Cyclical Behavior of Wages, Profits and Hours of Work

by

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Abstract

This thesis is composed of three essays. Chapter 1 analyzes the effect of time aggregation on estimates of the elasticities of output with respect to employment and to average hours of work. The main goal is to get accurate estimates of production function parameters. Low frequency data generate better estimates of output-employment elasticity while high frequency data generate better estimates of output-average hours elasticity. This result comes from the fact that time aggregation increases (decreases) the bias in the estimate of the elasticity with respect to average hours (employment). Estimations of these elasticities at different data frequencies and numerical simulations illustrate this point. In addition, this estimation methodology shows that the elasticity of output with respect to employment is bigger than the elasticity of output with respect to average hours, as theory predicts, contradicting an established result in the literature.

Chapter 2 tests the predictions of a neo-Keynesian model for the correlation of employment and wages using restrictions generated by the model to identify movements along or shifts in labor demand. Assuming nominal rigidities, a fixed labor demand, and instrumenting with unexpected aggregate demand shocks we estimate a labor demand elasticity around -1.0. The restrictions of the model also allow identification of a labor supply curve and we estimate a labor supply elasticity of close to 1.0. Then the assumption that the labor demand curve is relatively insensitive to product demand shocks is tested. The results are consistent with weak sensitivity of labor demand to these shocks. In particular, 4-digit industry data reject countercyclical markup models. The basic conclusions are threefold: First, the results show that nominal rigidities are an important transmission channel of aggregate demand shocks to real economic activity and there is no reason to reject the neo-Keynesian model based on the correlation of wages and employment. Second, the model and results provide a structural framework in which to interpret the sensitivity of traditional estimates of wage cyclicality to time period and deflator. Finally, the results raise questions about the ability of standard estimates of the correlation of wages and employment to measure the relative strength of aggregate demand and supply shocks, given that the choice of time period, deflator, and explanatory variables inherently biases the estimated cyclical coefficients toward identifying labor supply or demand.

In contrast to the first two chapters, the last one models the determination of employment and wages in the economy as a bargaining process between firms and workers. Using two standard bargaining models to illustrate the problems caused by the endogeneity of profits-per-worker in a real wage equation, it estimates the effect of firms' profitability on wage determination for the American economy. The chapter shows that the key parameter derived from the models, the profit-sharing coefficient, can be identified with instruments which shift sectoral demand for goods. Using information from the input-output table, demand-shift variables for 63 4-digit industries of the US manufacturing sector were created. The I.V. estimates show that profit-sharing is a relevant and widespread phenomenon. The elasticity of wages with respect to profits-per-worker is seven times as large as OLS estimates here and in previous papers. Sensitivity analysis of the profit-sharing parameter controlling for the extent of employees' unionization and product market concentration reinforces this basic result.

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It is not easy to live in a foreign country. It is even more difficult when one has a wonderful family like I do. Despite the distance of an entire hemisphere, my sisters and my brother were a constant source of support. My daughter, Gabriela, was probably the person that suffered most due to my long absences from Rio. Without her love and the many wonderful vacations we spent together, life in the US would have been too dreary and the doctoral degree would certainly not have paid off. Para a minha filhinha, todo o meu amor e um muito obrigado pela paciência.

Above all, my father's strength of character and courage when facing adversity inspired me during these years of hard work. His commitment to education is an example and a lesson that I shall never forget. As the culmination of my work as a student, it is particularly fitting that I dedicate this thesis to him.

To my father

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Chapter 1

Effects of Time Aggregation on Estimates of Output-Labor Elasticities

1.1 Introduction

Economists have been puzzled, in the last 30 years, by the observed large elasticity of output with respect to labor. Early studies focus their explanation on the existence of labor hoarding. Labor effort would vary in the short run when firms face economic shocks in order to compensate for the stickiness of employment. Because it is hard to measure labor effort, estimates of the elasticity of output with respect to labor would be inconsistent.[1] A second explanation is based on the unobservability of capacity utilization movements. The labor input is positively related to capacity utilization and the exclusion of this variable would cause the output-labor elasticity to be biased upward.[2] A third explanation accepts the existence of increasing returns to scale which is consistent with output-labor elasticities greater than one. This "fact" would

[1]Employment would be a quasi-fixed factor of production in the terminology of Walter Oi (1962). Some of these works are Brechling (1965), Ball and St. Cyr (1966) and Soligo (1966). They specify *ad hoc* dynamic equations for the production function in order to estimate long run output-employment elasticities smaller than one.

[2]Shapiro (1993), for instance, shows that accounting for variation in production shifts can solve the problem. Rotemberg and Summers (1989) argue that price rigidity may cause capacity underutilization and changes in capacity utilization may explain the evidence on increasing returns to scale. Abbott et al (1989) also present some evidence in favor of this argument.

explain firms' market power.[3]

The relevance of the empirical evidence in these works depends on the quality of the proxy variables for labor input and the instrumental variables used in their estimations. This chapter proposes a method to find the coefficients on employment and average hours in aggregate production functions. Accurate estimates of these coefficients are crucial to determine the total services of labor used in the production process. In addition to providing a more general specification for the production function, specifications where employment and average hours of work are considered separate inputs in the production process are important for a number of reasons. For instance, the sign and the size of the difference between both elasticities may help to explain the cyclical behavior of labor market variables, such as labor productivity and labor marginal cost. Another motivation for such a study comes from unemployment policy issues. The effect of labor-sharing policies, widely discussed in Europe now, which are based on an exogenous cut in average hours of work in an attempt to increase the employment level, also depends on this difference.

Previous studies provide estimates of the difference between the two elasticities. Table 1.1 lists the results. They all find that the output-employment elasticity is smaller than the output-average hours elasticity.[4] In this case, an increase in average hours and a compensatory decrease in employment, such that the total hours of work is constant, generates more output.

This result is far from being uncontroversial. If it is right, firms and workers are not taking advantage of the increasing returns of average hours on labor productivity. If these results are right and the hourly wage function is not highly sensitive to variations in average hours, firms would have an incentive to hire an infinite amount of average hours and almost no workers. Institutional constraints, such as the obligation to pay an overtime premium for hours worked in excess of 40 hours per week, may prevent firms from doing so. The next section builds a model that discusses this

[3]Hall (1988) shows that the joint hypothesis of increasing returns to scale and strong market power may be a good description of the American goods market.

[4]With the exception of Leslie and White (1980). This exception will be discussed in section 1.3.2.

Table 1.1: Previous results

Papers	Output-employment elasticity	Output-hours elasticity	Data
Feldstein (1967)	0.75 - 0.90	1.10 - 2.55	Annual data Cross-section UK
Craine (1973)	0.68 - 0.80	1.89 - 1.98	Annual data Time series US
Hart and McGregor (1987)	0.31	0.81	Semi-annual data Pooling of c.s. and t.s., Germany
Leslie and White (1980)	0.64	0.64	Same as Feldstein
Shapiro (1986)	1.00	1.06	Quarterly data Time Series US

effect and argues that firms and workers have economic incentives to contract a certain number of average hours of work which exhausts the increasing returns on total hours productivity of rearrangements in average hours and employment.

What would explain the high estimates for the output-average hours elasticity found by previous works ? I argue, in section 1.3, that the instrumental variables used in these papers are not good and that estimates of the difference between the two elasticities are inconsistent. In fact, there are no good instrumental variables for aggregate production function estimates. Because labor effort and capacity utilization are unobservable and firms hoard labor along the business cycle, as shown by Fay and Medoff (1985), instrumental variables related to exogenous demand shocks are not acceptable.[5] Furthermore, instruments that are possibly not correlated to supply or technological shocks, such as lagged endogenous variables, are correlated to the error term since it exhibits serial correlation.

Although there are no good instrumental variables available, the researcher must provide the best estimates possible. This chapter shows that, because employment and average hours present high variability at different frequencies (the first at low and the second at high sampling frequencies), and their correlation with the error term also changes depending on the data sampling frequency used, the large sample bias will differ for estimates using different data periodicity. The estimations reported here document this fact. Numerical simulations will show that monthly estimates for the elasticity of output with respect to average hours will be closer to the actual parameter value than estimates using more temporally aggregated data. The opposite is true for the elasticity of output with respect to employment. Using monthly estimates for output-average hours elasticity and annual estimates for output-employment elasticity, I show that the first is smaller than the latter. This result, at the same time, contradicts and explains the empirical evidence listed in table 1.1, since previous results were based on highly temporally aggregated data and used weak instrumental variables.

[5]So military expenditures, as used in Hall (1988), or demand shift variables based on input-output tables, as proposed by Shea (1993), are not appropriate here.

The chapter is organized as follows: The next section establishes the puzzle in the previous results discussed above. Section 1.3 gives some evidence on the dynamic behavior of employment and average hours to exogenous output shocks and provides estimates for both elasticities at different data frequencies. Section 1.4 considers the time aggregation effect explicitly and reports Monte-Carlo simulations showing that there is a bias in the aggregation process that explains the results obtained here and in the literature. The final section concludes this work.

1.2 Labor effort and hours of work

1.2.1 A model

This section builds a model that deals with the determination of hours and employment in the "long-run" (defined as the period of time when labor adjustment costs are not relevant). Its purpose is to provide a basic framework to characterize the relationship between labor effort and the output-employment and output-average hours elasticities in steady state.

First of all, for the sake of simplicity, assume a specific functional form for the production function :

$$Y_t = A_t \, S(N_t, H_t)^{\alpha} \, K_t^{\beta} \tag{1.1}$$

where, α and $\beta \leq 1$ and $S(\cdot) = N_t \, H_t \, J(H_t)$ is the total effort function, or services of labor function. $J(H_t)$, the effort function, also measures how far the average hours elasticity is from the employment elasticity.[6]

A general functional form for $J(H_t)$ is used:[7]

[6] The output-average hours elasticity can be written as $\alpha(1 + \epsilon_H^J)$ and the output-employment elasticity, α. So, the difference between both elasticities depends on the elasticity of effort with respect to average hours (ϵ_H^J).

[7] See also Estevão (1993).

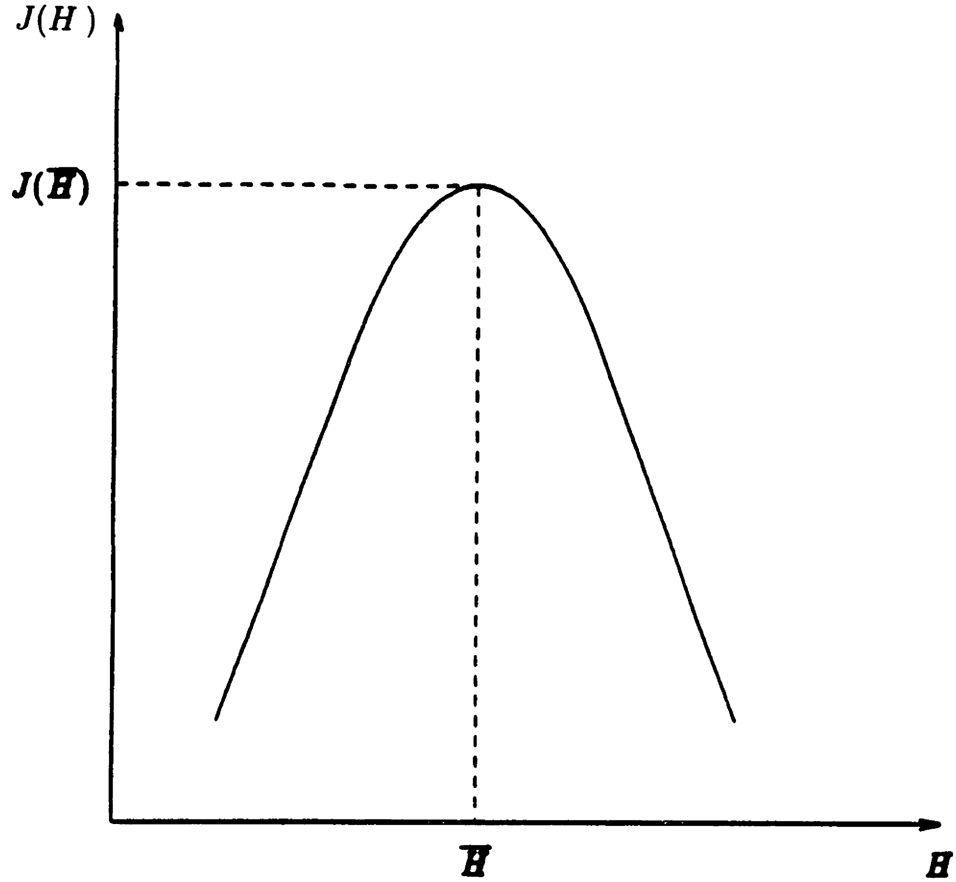

Figure 1-1: $J(H_t)$ function

$$J = J\left(H_t\right) \text{ , such that, } \left[\begin{array}{ll} \frac{\partial J(H_t)}{\partial H_t} > 0 & \text{if } H_t < \overline{H} \\ \frac{\partial J(H_t)}{\partial H_t} < 0 & \text{if } H_t > \overline{H} \end{array} \right. \tag{1.2}$$

This function traces out the relationship between average hours of work and labor effort. The fixed amount of time spent on beginning and finishing production, meals, the warming up process, instructions, and so on, generates a positive relationship between average hours and the $J(\cdot)$ function (Feldstein (1967)). Firms experience increasing returns in the labor services function if it decreases employment and increases the number of hours hired from each worker, for a given level of total hours hired. The fatigue caused by long hours of work generates the negative relationship. In this region, the services-of-labor function faces decreasing returns to average hours. The first set of effects are more relevant at lower levels of average hours of work and the fatigue effect is more important at higher levels of average hours of work. At $\overline{H}$ both effects cancel each other and $J(\cdot)$ has the form given in (1.2) and shown in figure 1-1.

In addition, it is assumed that firms face:

1. A downward sloping demand function:

$$P_t = \left(\frac{Z_t}{Y_t}\right)^{1-\frac{1}{\mu}} \tag{1.3}$$

   where, μ = mark-up; Z_t = demand shift parameter.

2. Two types of labor cost: $W(H_t)$ = hourly wage function ($\frac{\partial W}{\partial H} > 0$, $\frac{\partial^2 W}{\partial H^2} > 0$) and C = cost per worker.[8]

So, firms will maximize profit given equations (1.1), (1.3), the labor effort function and the labor cost variables. The choice variables are employment and average hours of work. The level of capital is given, by assumption.

Max. $\Pi = P(Y_t)\ Y_t - W(H_t)\ N_t H_t - CN_t$

s.t. (1.1) and (1.3)

From the first-order conditions:

$$\frac{W(H_t^*)\,H_t^*}{C} = \frac{1+\epsilon_H^J}{\epsilon_H^W - \epsilon_H^J} \tag{1.4}$$

where, $\epsilon_H^J = \frac{\partial J(H_t^*)}{\partial H_t^*}\frac{H_t^*}{J(H_t^*)}$ and $\epsilon_H^W = \frac{\partial W(H_t^*)}{\partial H_t^*}\frac{H_t^*}{W(H_t^*)}$, and

$$N_t^* = N(H_t^*, Z_t, A_t, K_t, \mu) \tag{1.5}$$

Notice that the optimal number of hours per person do not depend on demand parameters. Given the ratio between variable and fixed labor costs and the elasticities of the wage and the effort functions, firms decide the optimal number of hours hired from each employee. The level of employment is determined by the demand parameter, the mark-up, the technology parameter, the stock of capital and the optimal

[8]This parameter captures all expenses related to the labor force that are independent of the number of hours worked. I will assume that this variable is constant and given exogenously by some institutional arrangement. See Hart (1984) for an exhaustive discussion of the variables represented by C.

hours of work.[9] In a dynamic version ot this model, the average hours of work would change when demand varies (in the short run) to compensate for the stickiness of the employment level due to labor adjustment costs.

Equation (1.4) also shows that firms will choose average hours of work in the region where the labor effort elasticity is positive if the wage function is locally sufficiently sensitive to variations in hours.[10] In this case, the output-average hours elasticity ($\alpha(1 + \epsilon_H^J)$) will be greater than the output-employment elasticity (α).Otherwise, they will hire average hours until the increasing returns on the hourly productivity of a worker is exhausted, the effort elasticity is negative and the elasticity of output with respect to average hours will be smaller than the output-employment elasticity.

1.2.2 Are firms hiring too few hours?

The results reported in table 1.1 can be explained in the context of the present model if one of the two following conditions hold:

- the wage function is very steep at the hired level of average hours of work;
- firms would like to be hiring a larger number of work hours, but are prevented from doing so by some institutional constraint.

The first explanation suggests that firms do not hire more average hours of work because the disutility of an increase in labor effort causes an extra hour of work to be too expensive. Firms would increase the average number of hours hired if workers

[9]This fact is already well-known in the literature. Ehrenberg (1971) has proved this result for effort functions that are separable in N and H.

[10]The second-order conditions are, after some manipulations:

$$\alpha < \mu \tag{1.6}$$

the well-known condition establishing that the scale elasticity has to be smaller than the mark-up for the existence of an interior maximum. And,

$$\left(1+\epsilon_H^J\right)\left(1+\epsilon_H^W\right)\left(\epsilon_H^W-\epsilon_H^J\right) > \left(1+\epsilon_H^W\right)\frac{\partial\epsilon_H^J}{\partial H}H - \left(1+\epsilon_H^J\right)\frac{\partial\epsilon_H^W}{\partial H}H \tag{1.7}$$

Since, in general, $\frac{\partial\epsilon_H^J}{\partial H} \leq 0$ and $\frac{\partial\epsilon_H^W}{\partial H} \geq 0$, $\epsilon_H^W > \epsilon_H^J$ is also a sufficient condition.

were willing to work more at the same hourly wage rate. This is the *labor supply constraint* case.

The problem with this argument is that existing evidence shows that individuals are constrained to work fewer hours than the desirable level at the observed wage rate.[11] Because workers are hours-constrained in their supply of labor, the actual hourly wage function elasticity at this point should be close to zero. Additionally, Altonji and Paxson (1986) show that workers tend to move from one job to another in order to vary the number of hours worked. This evidence gives stronger support to the hypothesis that average hours of work at each job is determined by firms. Therefore, firms should stop hiring only if there is a negative effect on hourly effort.

The second explanation is the *institutional constraint* case. The Standard Fair Act (1935) mandates firms to pay a 50% overtime premium for employees working more than 40 hours per week. Even if employees were willing to work more hours at the same wage rate, firms would be prevented from hiring more hours from each worker because of the high marginal cost of an extra hour. A simplistic interpretation of this law would say that the extreme sensitivity of the wage function to variations in hours of work in this region would prevent firms from hiring more than 40 hours per week from each worker.

The basic problem with this explanation is that it assumes the law is effective and does not consider the economic incentives firms have to reorganize the production process to avoid the extra overtime costs.[12] For instance, firms could hire 10 hours of work per day during four days and not pay any overtime premium, instead of hiring 8.5 hours per day during five days and paying the overtime premium for the extra 2.5

[11]See Kahn and Lang (1988) and Dickens and Lundberg (1993), for instance.

[12]For the sake of simplicity, the model presented above does not make a distinction between daily and weekly hours. In practice, firms can rearrange daily average hours of work and the number of days worked. An example of such rearrangement can be found in The New York Times, 5/16/93: "Lacking enough demand, some manufacturers are finding ways to avoid both hiring and overtime. The Quaker Oats Company of Chicago, which now employs 11,000 Americans, down slightly in recent years, has shifted many of them to 10-hour daily shifts, four days a week - giving up overtime... ." The mechanism of determination of the number of days worked and the daily average hours of work, as well as their relationship with labor productivity, can be very interesting. This topic will be postponed for future research.

hours.[13]

Finally, firms and workers have the option of negotiating a straight-time wage that compensates the overtime premium. As argued in Hall (1980), the long term relationship between firms and their workers allows them to negotiate compensation schemes that map the disutility of effort (a continuous function of average hours) better than the discontinuous scheme proposed by the law. In this case, the shadow price of an overtime hour will be substantially smaller than the one stated in the law. Trejo (1991) documents this fact.

The issues discussed above lead us to expect that firms hire hours in the downward sloping region of the effort function.[14] But, the evidence presented in table 1.1 contradicts this *a priori* expectation. The next sections try to answer this puzzle.

1.3 Empirical strategy and results

1.3.1 The dynamics of employment and average hours adjustment to exogenous output shocks

Because firms face costs to adjusting the labor force when facing an exogenous output shock, average hours deviates from its static optimum level to compensate the sluggishness in employment.[15] The adjustment path of employment and hours to the new steady state depends on how expectations are formed, the nature of the shock (if it is permanent or temporary) and the type of labor adjustment costs. However, for any specification of these variables, average hours should return to its old steady-state level once the effect of the output shock is over, because they are scale insensitive.

[13]The idea is that firms will be able to use less total hours of work to produce a given amount of output since they will be exhausting all the "increasing returns" coming from increases in average daily hours/worker. In this example it is assumed that firms can produce the same level of output using 40 hours/worker per week and 10 hours/worker daily (what makes $\epsilon_H^J \leq 0$) or using 42.5 hours/worker per week and 8.5 hours/worker daily (what makes $\epsilon_H^J > 0$).

[14]One last reason for this prior is just casual observation. In general, people perceive a decrease in their hourly work productivity at the end of a regular working day.

[15]Here I am considering output as an exogenous variable to simplify the argument. In other words, firms are demand constrained.

Therefore, although average hours is very sensitive to output variations at high frequencies, as long as the nature of the shock is uncertain, it will be basically insensitive to them at lower frequencies. By the same reasoning, employment should vary more at low than at high frequencies.

In order to see if this dynamic response is present in the data used here, I ran a reduced form VAR system of output, employment and average hours, represented in equations (1.8) and (1.9). This system imposes a smooth adjustment process on the data and is basically *ad hoc*, but it captures the raw correlations between output and employment and between output and average hours at high frequency and after the adjustment process is completed.

$$\Delta n = c_1 + \Theta_1(L)h + \Psi_1(L)\Delta n + \Lambda_1(L)\Delta y + \nu_1 \tag{1.8}$$

$$h = c_2 + \Theta_2(L)h + \Psi_2(L)\Delta n + \Lambda_2(L)\Delta y + \nu_2 \tag{1.9}$$

The system was estimated in first differences for employment and output because these variables are integrated of order 1 and the average hours variable is integrated of order zero.[16] Figure 1-2 shows that the initial response of employment to a one percent permanent shock in output is small but it increases over the course of the adjustment process. On the other hand, average hours are initially sensitive to variations in output, but as the shock works through the system, they return to their initial level as illustrated in figure 1-3.[17]

Because of the dynamic adjustment of employment and average hours, the degree of correlation between these variables and other inputs, capacity utilization, and labor hoarding, varies depending on the data frequency chosen. At high frequencies average hours will track capacity utilization and labor hoarding more closely than

[16] In equations (1.8) and (1.9), $x = log(X)$ and Δx = first difference of x. The estimations use monthly data for the American manufacturing sector and 6 lags for each of the three variables. The result is robust to changes in the lag order. The appendix to this chapter describes the database used here.

[17] Notice that these responses do not allow for a feedback in output. The approach used here considers output as an exogenous variable. The short and long-run responses of employment and average hours to output shocks are not affected if a feedback in output is allowed.

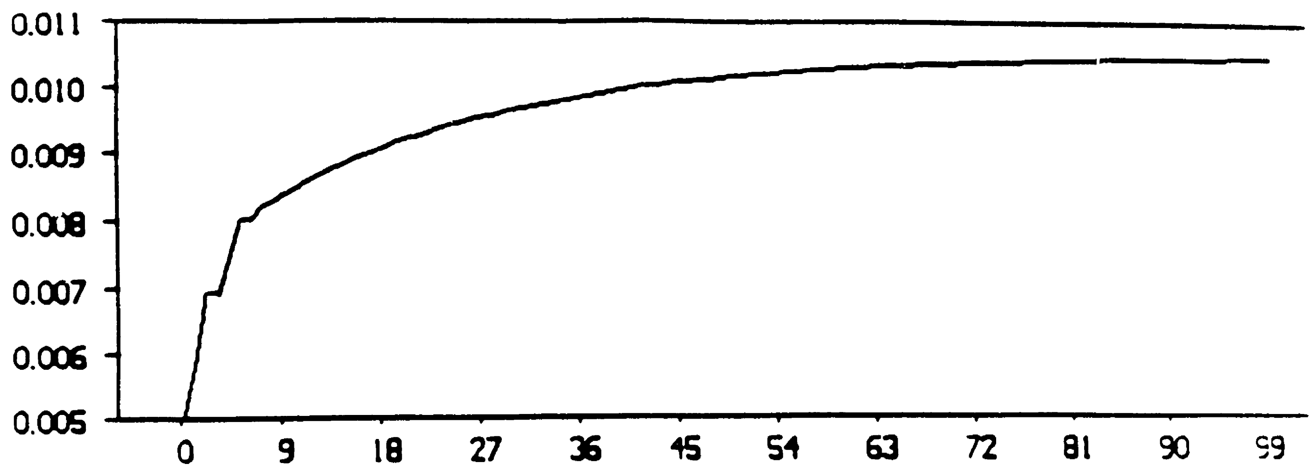

Figure 1-2: Employment responses to a one percent permanent shock in output

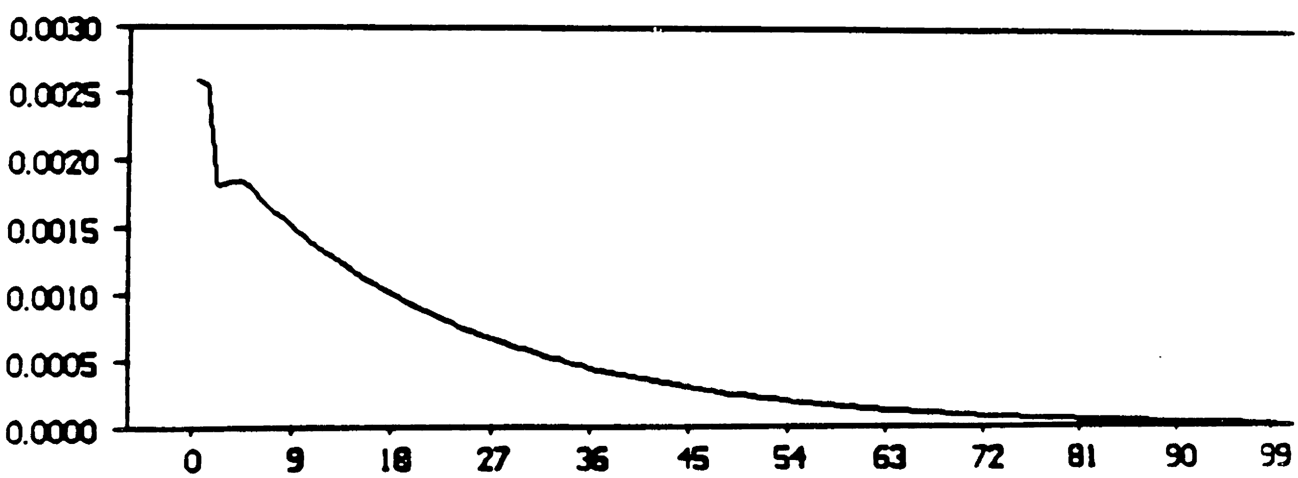

Figure 1-3: Average hours responses to a one percent permanent shock in output

at low frequencies.[18] Employment will also be correlated to both variables at high frequencies. At low frequencies employment will be more correlated to other inputs, such as capital stock and raw materials, than average hours is. Additionally, the variance of average hours is larger at high frequencies than at low frequencies. The reverse is true for employment.

These dynamic effects make the choice of data frequency for estimations of output-labor elasticities non-trivial. This assertion can be explained by the following sequence of arguments:

1. production function estimations tend to exclude some relevant non-observable regressors, such as capacity utilization, the actual number of hours used in the production process, as opposed to the hired number of hours, and other raw materials;

2. the covariance between both employment and average hours and these excluded variables change with the data frequency used;

3. the variance of both employment and average hours also changes depending on the data frequency used;

4. given the first three arguments, the bias in the OLS estimator, caused by the correlation between both regressors and the excluded variables, will also change at each frequency. Given that instrumental variables are not perfect, in the sense that it is expected that they present some correlation with the error term, the same reasoning can be applied to the IV estimator.[19]

[18]The next section will define the labor hoarding variable more precisely.

[19]The large sample bias of estimates of both elasticities can be written as,

$$bias(\beta_{IV}) = \frac{f(cov(\hat{n},\epsilon), cov(\hat{h},\epsilon), \cdot)}{g(cov(\hat{n},n), cov(\hat{h},h), \cdot)}$$

where $\hat{x}$ represents the first stage fit of variable x, using a set Z of instruments, and ϵ is the regression error. When Z is composed of the regressors themselves this is the formula of the bias in the OLS estimator. Let us call this formula the "signal-to-noise ratio". The bigger is the correlation between the instruments and the component of the regressors that is correlated to the error term, the closest to the OLS estimator is the IV estimator. The bigger is the correlation between the instruments and the regressors the smaller is the bias.

Because average hours is supposed to be more correlated to these omitted variables and to have higher variance at high frequencies, it is not clear which is the best data periodicity for estimation purpose. The same argument can be made for employment. In summary, there is no reason to get equal parameter estimates when using different data frequencies, if the instrumental variables are not perfect. The next subsection provides estimations that support this view. Section 1.4 will show numerically that the pattern of the signal-to-noise ratio at different data frequencies will give guidance on the best data periodicity for estimation purposes.

1.3.2 Econometric methodology and results

The basic methodology used here departs from the assumption that firms always work on their production function. In order to test for the existence of an estimation bias caused by the use of time-aggregated data, I will estimate output-employment and output-average hours elasticities using different data frequencies.[20]

Let us write the production function as:

$$Y_t = F(A_t, S(N_t, \tilde{H}_t), O_t) \tag{1.10}$$

where N_t is the employment level, $\tilde{H}_t$ is the average hours of work, O_t represents other inputs used in the production process and is not explicitly included in the equation studied; $A_t = e^{ct+r_t}$, with c as a constant, and r_t a mix of technology and other exogenous shocks. For estimation purposes, it is assumed that $J(\cdot)$ can be locally approximated by a constant elasticity function:

$$J\left(\tilde{H}_t\right) = \tilde{H}_t^{\,\theta} \tag{1.11}$$

Letting $x = log(X)$, $F_X = \frac{\partial F}{\partial X}$, and taking total derivatives of (1.10), yields:

[20] This is also a test on the quality of the instruments used at different frequencies. As argued in the past section, if the instruments were perfect the estimates at each frequency would be identical. Because I use the same instrumental variables used in the papers listed in table 1.1 I will be able to say something about the quality of previous results.

$$my_t = \frac{F_S S_t}{Y_t} ds_t + \frac{F_O O_t}{Y_t} do_t + \frac{F_A A_t}{Y_t} da_t$$

Assuming that $\frac{F_S S_t}{Y_t} = \alpha$, $\frac{F_O O_t}{Y_t} = \frac{F_A A_t}{Y_t} = 1$, gives:

$$dy_t = c\,dt + \alpha\,dn_t + \alpha(1+\theta)\,d\tilde{h}_t + do_t + dr_t$$

Then given that O_t is non-observable the discrete time version of the equation to be estimated is:

$$\Delta y_t = c + \alpha\,\Delta n_t + \lambda\,\Delta \tilde{h}_t + e_t \tag{1.12}$$

where, $e_t = \Delta o_t + \Delta r_t$; and, $\lambda = \alpha(1+\theta)$.

The existence of labor hoarding (see Fair(1969) and Fay and Medoff (1985)) implies that actual average hours of work will be different from the paid (and observed) average hours. This effect is modeled here as a measurement error in the actual hours worked, where the error is negatively correlated to the actual variable. Formally, let h_t be the (log of) hired average hours, and $\sigma_{xy} = Cov(\Delta x, \Delta y)$ then:

$$h_t = \tilde{h}_t + \xi_t$$

where $\sigma_h^2 < \sigma_{\tilde{h}}^2$; $\sigma_{\tilde{h}\xi}$, $\sigma_{h\xi}$ and $\sigma_{n\xi}$ are negative.

Finally, the equation estimated is:

$$\Delta y_t = c + \alpha\,\Delta n_t + \lambda\,\Delta h_t + \nu_t \tag{1.13}$$

where, $\nu_t = e_t - \lambda\,\Delta\xi_t$.

The OLS estimators for both elasticities will be inconsistent for several reasons. First, output and inputs will be adjusted simultaneously when input prices change or when there is a technological shock. The direction of this simultaneity bias is not known *a priori* and I will assume that the instrumental variables chosen in the estimations reported below solve this problem.

Second, the existence of labor hoarding creates a positive correlation between the error term and the regressors. The absence of other relevant inputs also causes a positive correlation between the regressors and the errors, because these inputs tend to covary positively with capacity utilization. Equations (1.14) and (1.15) are the probability limits of the OLS estimator. It is also assumed that $E[\Delta n] = E[\Delta h] = 0$ for the sake of simplicity.

$$plim\,(\alpha_{ols} - \alpha) = \frac{\sigma_h^2 \sigma_{n\nu} - \sigma_{nh}\sigma_{h\nu}}{\sigma_n^2 \sigma_h^2 - \sigma_{nh}^2} \tag{1.14}$$

$$plim\,(\lambda_{ols} - \lambda) = \frac{\sigma_n^2 \sigma_{h\nu} - \sigma_{nh}\sigma_{n\nu}}{\sigma_n^2 \sigma_h^2 - \sigma_{nh}^2} \tag{1.15}$$

where the denominators of these expressions are positive by the Schwarz inequality.

Without more information on the magnitudes of each term in both equations, the direction of the bias caused by the existence of labor hoarding and omitted inputs is not clear. I will analyze the direction of the bias at different data frequencies in section 1.4. For now it is enough to know that the estimation of equation (1.13) requires the use of instruments for the regressors.

Table 1.2 shows estimations of equation (1.13) using time series of US aggregate manufacturing data.[21] The output-average hours elasticity is smaller than the output-employment elasticity if the equation is estimated using monthly data. Furthermore, the size of this elasticity increases the more temporally-aggregated is the data. The estimations using annual data match previous comparable results.[22] Time aggregation seems also relevant for estimations of α, although they follow an opposite pattern, where $\hat{\alpha}$ decreases with time aggregation. [23] [24]

[21]The data appendix discuss the problems with the database, focusing on measurement errors in the variables, as well as their impact on the estimates.

[22]See Crane (1973) in table 1.1, for instance. He also uses data for the American manufacturing sector.

[23]This pattern remains the same if data aggregated into 4 and 6-months frequencies are used. These results were excluded because these data periodicities are not commonly used in economics.

[24]Notice that the R^2 reported in the first three rows of table 1.2 increases with time aggregation. As it was first proved by Zellner and Montmarquette (1971), this is purely a mathematical result

Table 1.2: Regressions for aggregate manufacturing data

Frequency	Constant	α	λ	Method	R^2
Monthly	.0031	1.0384	.5573	OLS	.7338
	(11.59)	(30.96)	(12.71)		
Quarterly	.0093	.9506	1.1286	OLS	.9011
	(15.38)	(22.22)	(10.37)		
Annual	.0375	.8365	1.4670	OLS	.9713
	(20.99)	(16.11)	(8.28)		
Monthly	.0031	1.0560	.3674	IV	First set of
	(11.43)	(16.21)	(3.52)		instruments
Quarterly	.0092	.8133	1.4534	IV	
	(14.56)	(14.16)	(7.36)		
Annual	.0376	.9701	1.2189	IV	
	(19.49)	(10.45)	(4.24)		
Monthly	.0031	.9717	.6405	IV	Second set of
	(11.43)	(24.99)	(12.40)		instruments
Quarterly	.0093	.9316	1.1525	IV	
	(15.14)	(19.62)	(9.85)		
Annual	.0375	.8517	1.3970	IV	
	(20.96)	(15.00)	(7.23)		

Notes:

1. t-statistics in parenthesis.
2. Sample sizes: monthly estimations, 1947:02 to 1992:11; quarterly estimations, 1947:2 to 1992:3; annual estimates: 1948 to 1991.
3. The first set of instruments includes a constant, lags of employment, average hours and real wage. The second set of instruments is composed of a constant, rank variables for employment and average hours, and lag of order 1 for the real wage.

The estimations using instrumental variables generate the same result. The first set of estimates uses lags of employment, average hours and real wages as instruments.[25] The R^2 of the first stage regressions range from .2 to .55. However, the residuals of the estimated equation are serially correlated indicating that these variables are, possibly, not good instruments. One possible source of serial correlation could be omitted inputs that face adjustment costs. Previous papers also use lags of explanatory variables as instruments.[26]

Rank variables for employment and average hours and lags of the real wage variable are also used as instruments. [27] The rank variables are certainly correlated to the regressors but nothing definite can be said about their correlation with the error term. The results show the same pattern as the OLS estimations.

I test the restrictions that both elasticities are the same. The F-test rejects the null hypothesis of equality between them when monthly and annual data are used.[28] It is therefore relevant to consider both variables separately in the production function, at least at those frequencies.

Table 1.3 presents annual regressions including the capital stock. The results remain more or less the same. Estimates of the elasticity of output with respect to

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generated by the aggregation process. It can be shown, using the aggregation matrix described in the next section, that the R^2 for estimations of the model above using quarterly data (R_q^2) can be written as:

$$R_q^2 = \frac{R_m^2}{R_m^2 + \Upsilon(1 - R_m^2)}$$

where, $R_m^2 = R^2$ obtained by monthly estimations of the model and

$$\Upsilon = (1 + \frac{32}{19\rho_1} + \frac{20}{19\rho_2} + \frac{8}{19\rho_3} + \frac{2}{19\rho_4})^{-1}$$

The ρ_i's are the autocorrelation coefficients for the independent variable in equation (1.13). Since these autocorrelations are positive, in the case studied here, the result is immediate.

[25] I use lags until order three for the monthly and quarterly estimations and just the first lag of these variables for the annual estimations. The pattern of the estimates remains the same independent of the number of lags chosen for the instruments.

[26] See, Feldstein (1967), Leslie and White (1980) and Abott, Griliches and Hausman (1988), for instance.

[27] The same variables were used as instruments in Feldstein (1967), Leslie and White (1980) and Hart and McGregor (1988). Rank variables go from 1 to T, the number of observations, with step size equal to one, and order the respective data series from its smallest to its highest value.

[28] The statistics at the three data frequencies in the OLS estimations are: $F_m(1,547) = 61.96$, $F_q(1,179) = 1.55$ and $F_a(1,41) = 8.15$. The constraint is equally rejected for the IV estimations.

Table 1.3: Annual regressions for aggregate manufacturing data with capital stock

Constant	α	λ	Output-Capital elasticity	Method	R^2
.0315 (12.57)	.790 (16.95)	1.458 (9.43)	.215 (3.46)	OLS	.9804
.0312 (10.61)	.813 (12.63)	1.396 (7.96)	.209 (2.47)	IV	First set of instruments
.0319 (11.79)	.791 (15.75)	1.434 (8.63)	.2046 (2.92)	IV	Second set of instruments

Notes:

1. t-statistics in parenthesis.
2. Sample size: 1948 to 1991.
3. The first set of instruments includes a constant, lags of order 1 of employment, average hours and real wage, and lags of order 1 to 8 of the capital stock. The second set of instruments is composed of a constant, rank variables for employment, average hours and capital, and lag of order 1 for the real wage.

employment are slightly smaller than the ones presented in table 1.2 but the output-average hours elasticity is basically the same. Because there are no data on monthly capital stock and the quarterly data are not reliable, I did not run regressions including the capital stock at these frequencies. The results presumably would not change much if these regressions were performed since the capital stock is not very sensitive to high frequency shocks.

Table 1.4 reports estimates using a pooling of time series and panel data for 2 digit-manufacturing sectors. The coefficients for employment and average hours are forced to be the same in each sub-sector and sectoral dummies are introduced to capture sectoral differences in productivity.[29] These dummies correspond to the time slope dummies in Leslie and White (1980), since the equation estimated here is specified in first differences, while they estimate a similar equation in levels. Rank variables of the regressors and lags of the real wage were used as instruments. The results are

[29]The coefficients for the dummy variables are omitted to save space.

basically the same if lagged endogenous variables are used as instruments. Although an F-test rejects the restriction that the coefficients are the same for each sector, the estimated coefficients give some information on the average output-employment and output-average hours of work elasticities.

This set of regressions tries to capture some of the effect of sectoral aggregation on elasticity estimates. Using a British database, Leslie and White (1980) test the hypothesis that more productive sectors also hire more hours from their workers. In this case, the coefficient of average hours of work will be biased upwards. They found that, once sectoral aggregation is taken explicitly into account, the elasticity of output with respect to average hours of work declines and becomes the same as the output-employment elasticity (see table 1.1). I could not replicate the same effect for the manufacturing sector in the US, although the estimates for the output-employment elasticity are smaller at each frequency than the ones reported in table 1.2. Hart and McGregor (1988) could not find a sectoral aggregation effect on the output-average hours elasticity for the German manufacturing sector either. But, they found that the elasticity of output with respect to employment falls, as well.

As discussed in the beginning of this section, different estimates of both elasticities at each data frequency is consistent with the fact that changes in employment and average hours have different variances and covariances with the residual at different frequencies. This result is also evidence that the instrumental variables used here and in previous papers are correlated to the error term in at least two of the three data frequencies. In this case, the IV estimations just replicate the OLS estimations. Therefore, the usual claim in this literature that the IV estimations present similar results as the OLS estimations should be viewed with caution.[30] In the next section, I will show that the pattern obtained for estimates of both elasticities at different data frequency can be explained by the effect of time aggregation on the signal-to-noise ratio.

[30]See Leslie and White (1980), Feldstein (1967) and Hart and McGregor (1988).

Table 1.4: Restricted regressions for panel of 2-digit sectors

Frequency	α	λ
Monthly	.9159	.6574
	(29.58)	(15.14)
Quarterly	.8041	1.1741
	(24.66)	(14.10)
Annual	.7441	1.6262
	(35.00)	(27.13)

Notes:

1. t-statistics in parenthesis.
2. Sample size: monthly estimations, 1947:2 to 1992:03; quarterly estimations, 1947:02 to 1992:01; annual estimations, 1948 to 1991.
3. The set of instruments is composed of a constant, rank variables for employment and average hours, and lag of order 1 for the real wage.

1.4 The temporal aggregation effect

The basic problem of analyzing the signal-to-noise ratio at each frequency is the unobservability of the correlation between the regressors and the error term. In order to overcome this problem, I will model explicitly the time aggregation process. The final bias equation will depend on the variances, autocovariances, and covariances between lags and leads of the regressors and the residuals when evaluated using monthly data. The advantage of this methodology is that, given the autocorrelation and cross-correlation functions for these variables at monthly frequency, it is possible to assess the bias at lower frequencies and evaluate the effect of time aggregation without having to assume explicitly a different value for the correlation between the regressors and the residuals.

First, let us write equation (1.13) in matrix format:

$$\Delta y = X\beta + \nu \tag{1.16}$$

$X = [\ 1\ \ \Delta n\ \ \Delta h\ ]\ ;\ \nu = e - Q\beta\ ;\ Q = [\ 0\ \ 0\ \ \Delta Q\ ]$ and $\beta = [\ c\ \ \alpha\ \ \lambda\ ]'$.

Define $M_{G\times T}$, as the aggregation matrix:

$$M = \begin{bmatrix} 1 & 2 & \dots & n-1 & n & n-1 & \dots & 1 & 0 & \dots & 0 & 0 & \dots & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 & \dots & n-1 & n & \dots & 1 & 0 & \dots & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 & \dots & 1 & \dots & n-1 & n & n-1 & \dots & 1 \end{bmatrix}$$

This matrix takes the T observations of a first difference data at periodicity 1 and transforms them into G observations of first difference data at periodicity n. So the equation to be estimated using data with periodicity n is:

$$M\Delta y = MX\beta + M\nu \tag{1.17}$$

For instance, the M matrix for the quarterly aggregation case is:

$$M = \begin{bmatrix} 1 & 2 & 3 & 2 & 1 & 0 & 0 & 0 & 0\dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 2 & 3 & 2 & 1 & 0\dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\dots & 0 & 1 & 2 & 3 & 2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\dots & 0 & 0 & 0 & 0 & 1 & 2 & 3 & 2 & 1 \end{bmatrix}$$

Equation (1.17) represents estimations using data observed at each n periods. When $n = 1$, $M = I_{T\times T}$. The OLS estimator for β using aggregated data is:

$$\beta_{ols} = (X'PX)^{-1}X'Py = \beta - [X'PX]^{-1}[(X'PQ)\beta + X'Pe]$$

where, $P = M'M$.

Because, $corr(X, Q)$ and $corr(X, e) \neq 0$, β_{ols} will be an inconsistent estimator of β. The probability limits for α_{ols} and λ_{ols} when time-aggregated data are used are:

$$plim(\alpha_{ols} - \alpha) = \frac{\sigma_h^2\sigma_{n\nu} - \sigma_{nh}\sigma_{h\nu} + \phi_1}{\sigma_n^2\sigma_h^2 - \sigma_{nh}^2 + \phi_2} \tag{1.18}$$

$$plim(\lambda_{ols} - \lambda) = \frac{\sigma_n^2 \sigma_{h\nu} - \sigma_{nh}\sigma_{n\nu} + \phi_3}{\sigma_n^2 \sigma_h^2 - \sigma_{nh}^2 + \phi_4} \tag{1.19}$$

The σ_{ij} terms are the variances and covariances of the high frequency observations. The bias term is the same as before except for the ϕ_is which involve terms composed of cross-correlations and autocorrelations of lags and leads of regressors and errors, multiplied by coefficients determined by the degree of temporal aggregation. These coefficients depend on matrix M. The ϕ_is will determine the direction of the aggregation bias. For instance, if Δn, Δh, $\Delta \xi$ and e are i.i.d. the size of the bias is the same for all the data frequencies used. In general, the bias in estimates of β at each frequency will vary.

One way to check if time aggregation matters is to compute the probability limits for both elasticities when estimated at different frequencies. These limits can be evaluated using the observable variances and covariances between the regressors and their lags, and the assumptions on their correlation with the error term. There are two problems with this approach. First, it is computationally burdensome. The ϕ terms in equations (1.18) and (1.19) will be more complex and will involve higher-order lag correlations the larger is the degree of time aggregation. Second, the result would be valid when the number of observations tends to infinity but imperfect in small samples.

In order to handle both problems, I perform Monte-Carlo simulations. Their basic structure can be described as follows:

- first, 550 random data points are generated for Δn, Δh and ν assuming that these variables have a joint multivariate normal distribution with a variance-covariance matrix, Σ;[31]

- second, Δy is generated under the assumption that $\alpha = .75$ and $\lambda = .40$. Dif-

[31]The variances and covariances of Δn and Δh and their lags and leads are observed. I impose different identifying assumptions on the covariances between regressors and the residual term at monthly frequency. Furthermore, Σ is constrained to be positive definite. The variance of ν were such that it matches the variance of the residuals of the estimated equation for the manufacturing sector.

ferent initial values for β were used but the pattern of the estimates at different data frequencies is the same.[32] At this point, equation (1.17) is estimated "at monthly frequency";

- third, using matrix M, I obtain the quarterly and the annual data for Δy, Δn and Δh and perform estimations of β at these frequencies;
- finally, this process is repeated 1000 times.

The basic identifying restriction is that estimates of both elasticities at monthly frequency are positively biased. As the Monte-Carlo simulations show, this restriction is satisfied by a large number of combinations of $\sigma_{n\nu}$ and $\sigma_{h\nu}$.[33] The pattern of the estimates reported in the last section are replicated for any parameter randomly chosen in the region defined by the identifying restrictions. Table 1.5 reports a representative result in the region were $\sigma_{h\nu} > \sigma_{n\nu}$. The only criteria used to choose this specific simulation is that $\sigma_{n\nu}$ and $\sigma_{h\nu}$ are of the same order of magnitude as σ_{nh}.[34]

Simulations in the region where $\sigma_{h\nu} < \sigma_{n\nu}$ can be represented by the simulation reported in table 1.6.[35] The results show the same pattern as the ones presented

[32]These values seem reasonable based in the results reported in section 1.3.2, if what is driving the results when low frequency data is used is an aggregation effect that increases the positive bias in the output-average hours elasticity estimates and decreases the positive bias in the output-employment elasticity estimates.

[33]Using the observed values of σ_n^2, σ_h^2 and σ_{nh} to establish restrictions on $\sigma_{n\nu}$ and $\sigma_{h\nu}$ such that (1.14) and (1.15) are positive leads to :

$$\frac{1.23}{6.85} < \frac{\sigma_{h\nu}}{\sigma_{n\nu}} < \frac{4}{1.23}$$

So, monthly estimates of both elasticities will not be upward biased if one of the covariances is substantially bigger than the other one. Given that at monthly frequency both variables are expected to be significantly correlated to labor hoarding and capacity utilization this alternative does not seem plausible.

[34]Obviously, if both covariances are too small there is no significant bias in the estimates. In this case, the estimates at different frequencies should not differ from each other what contradicts the OLS results presented before. The variance-covariance matrix used in table 1.5 was built using the observed variance-covariance matrix for n and h, assuming that $\sigma_{n\nu} = 5 * 10^{-6}$, $\sigma_{h\nu} = 1 * 10^{-5}$, and $\sigma_\nu^2 = 4 * 10^{-5} = \sigma_h^2$ (observed in the data). Additionally, the lag correlations between the residual and the regressors were assumed to decline fast to zero. Different assumptions on the shape of these cross-correlations generated minor changes in the results. Each of these assumptions correspond to a particular model for labor hoarding.

[35]If $\sigma_{h\nu}$ is very low such that the output-average hours elasticity is underestimated at monthly frequency, the use of time-aggregated data will cause the bias to be even more negative. The

Table 1.5: Monte-Carlo simulations - $\sigma_{n\nu} < \sigma_{h\nu}$

	β_i	β_1	β_3	β_{12}
constant	.003	.003 (.000)	.028 (.003)	.445 (.043)
α	.75	.806 (.034)	.723 (.045)	.721 (.064)
λ	.40	.764 (.050)	.939 (.162)	1.126 (.349)
R^2	—	.604	.714	.825
Number of obs.	—	550	182	44

Note:Std. deviations of the coefficients in parenthesis.

in table 1.5. In fact simulations in this region tend to fit the data better, since the higher covariance between employment and the error term increases (decreases) the bias in monthly estimates of output-employment (average hours) elasticity.[36]

Since nothing was assumed explicitly about the correlation between the regressors and the residual term at lower frequencies, this exercise provides strong evidence in favor of a time aggregation bias. The larger is the degree of temporal aggregation, the more distorted are estimations of the output-average hours elasticity. On the other hand, the larger is the degree of temporal aggregation the less distorted are estimations of output-employment elasticity. The simulations show that, although the bias in estimates of output-employment elasticity can be very large at monthly frequency, they are very stable at annual frequency. The simulated value for this elasticity using annual aggregation does not depend much on parameter choice.

The slight negative bias in the simulations of the output-employment elasticity at quarterly and annual frequency should be viewed as an exclusive consequence of temporal aggregation. Notice that the Monte-Carlo simulations do not take into

simulations will also change if the correlation between employment and the residual are too low. But, as said before these cases do not seem plausible.

[36]The variance-covariance matrix used in table 1.6 is basically the same as the one used in table 1.5. The difference is that I assume that $\sigma_{n\nu} = 1 * 10^{-5}$ and $\sigma_{h\nu} = 5 * 10^{-6}$. The results are also robust to different assumptions on the ν process.

Table 1.6: Monte-Carlo simulations - $\sigma_{n\nu} > \sigma_{h\nu}$

	β_i	β_1	β_3	β_{12}
constant	.003	.003	.028	.448
		(.000)	(.002)	(.036)
α	.75	.856	.767	.731
		(.035)	(.037)	(.048)
λ	.40	.475	.732	1.212
		(.040)	(.127)	(.312)
R^2	—	.654	.766	.860
Number of obs.	—	550	182	44

Note:Std. deviations of the coefficients in parenthesis.

account variables that are positively correlated with employment at this frequency but are not included in the regression.[37] So the actual estimates for the elasticity of output with respect to employment are probably biased upward. The aggregation effect seems to be stronger than the correlation effect because the estimated elasticity falls with time aggregation.

1.5 Conclusions

The simulations described in the past section show that, assuming a positive bias in monthly estimates of output-employment and output-average hours elasticities, a time aggregation effect can explain the results obtained in section 1.3.2. Temporal aggregation increases the positive bias in estimates of output-average hours elasticity. On the other hand, it decreases the positive bias in estimates of output-employment elasticity. In this case, the monthly estimate of the elasticity of output with respect to average hours is closer to the actual parameter. The output-employment elasticity

[37]As table 1.3 shows, when the capital stock is included in the estimated regression at annual frequency the output-employment elasticity decreases slightly. In fact the same argument can be made for the elasticity of output with respect to average hours. Feldstein (1967), for instance, shows that the estimate of this elasticity falls when measures of capacity utilization are included in his annual regressions, but it is still much bigger than output-employment elasticity.

is more accurately estimated when annual data is used. Therefore, using the elasticities estimates at these frequencies reported in section 1.3.2, this chapter shows that the output-average hours elasticity is smaller than the output-employment elasticity. This finding contradicts the evidence of previous works. Additionally, these previous results can be explained by the time aggregation effect since they were built using annual, semi-annual or quarterly data and the same instrumental variables used here.

The estimation problems studied here have a general flavor. Whenever the regressors in a equation present a dynamic pattern of adjustment, which means that their covariance, as well as, their variances change at different data frequencies, the parameter estimates will also change as long as there is a correlation between the regressors and the residual term. The problem is even bigger if there is a chance that this correlation also varies at different data frequencies. If the instrumental variables used in the estimation are not perfect or close to perfection, the problem will not go away with IV estimations.

A similar methodology to the one used here can be applied to decide the right data periodicity for the estimation process. Specifications using different data frequencies can reveal information on the quality of the instrumental variables used and on the direction of the bias. Simulations using the observed variance-covariance matrix of the regressors and identifying assumptions on the origin of the correlation between regressors and the residual term, may point to the direction of the time aggregation bias. These simulations can be used to facilitate the choice of the data frequency that generates the most accurate parameter estimates.

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1.7 Appendix: Data problems and database description

The database used in this chapter is composed of:

- a sectoral production index calculated by the Board of Governors of the Federal Reserve System (FED). This seasonally adjusted index is available since January, 1947;

- data on production workers, average weekly hours of production workers, gross average hourly earnings of production workers and consumer price index calculated by the Bureau of Labor Statistics (BLS). These data are available since January of 1947. Only data on employment and average hours is seasonally adjusted.

- the capital stock series is the "Equipment and Structures" annual series for the manufacturing sector calculated by the Department of Commerce, BEA.

The data on seasonally-adjusted real hourly earnings were obtained by regressing real gross average hourly earnings on seasonal dummies and then using the forecast errors, weighted by a smoothing parameter to get a smoothed series.

There are some basic problems with the data. First, there is measurement error in the output data. The FED index of industrial production tries to capture changes in physical volume in each sector. Since there is no measure of physical volume for some industrial goods, however, the information for these categories was inferred from input data: production-hours worked (BLS), employment (BLS) and kilowatt-hours consumed (FED). This will tend to produce an identity relation between total hours of work and output for these goods categories. Data based on total hours of work or employment correspond to 25.2% of total industrial production, while 30.0% are based on kilowatt-hours consumed and 42.9% on pure physical output data. The remaining uses a combination of employment, total hours of work, and kilowatt-hours consumed. Some sectors have a higher proportion of imputed information than others. The results reported here do not seem to be biased in a particular way for this reason. Additionally, sectoral regressions present the same pattern as the ones reported in the text, independently of the proportion of imputed information in the output series.[38]

The same regressions were performed for selected 2-digit sectors and the whole manufacturing sector using an alternative data for physical output. This data was built using the Bureau of Commerce data on sales and inventories variation. The results follow the same pattern as the ones reported here, but present much stronger serial correlation problems and the estimated parameters are more sensitive to the choice of instruments.

Second, there are important methodological differences among the series used. Components of each sectoral output index are adjusted for monthly differences in the number of working days. Reported product data are converted to a daily average basis by adjusting for the number of working days in the reporting period. The employment and average hours data include all full-time and part-time workers who received pay for any part of the pay period that includes the 12th day of the month. This causes a mismatch between these data, basically a weekly data, and the output data, that refer to the whole month.[39] So, output data is a smoother version of the appropriate data (if it is considered the sampling methodology for employment and hours data as "appropriate"). Furthermore, holidays are seasonal. Since, employment and average hours series are weekly samples of monthly data it is possible to have "bad seasonality" in the sense that variation in output per month may not be reflected in the labor data. Given these problems it is crucial to deseasonalize the data.

It is worth noticing that the use of deseasonalized data in production function estimates is not undisputable. Fair (1969), for instance, argues that the production function is a representation of the technical relationship between inputs and output and not between "deseasonalized input" and "deseasonalized output". But, the data structure does not give a better research alternative and all estimations are carried on with the deseasonalised data provided by the FED and the BLS.

[38]The sectoral results are available upon request.

[39]A similar discussion can be found in Sims (1974).

This difference in the sampling methodology causes an additional problem. Bresnaham and Ramey (1994) show that firms frequently use production shutdowns as a way to achieve production goals. If there is a production stoppage in the week that contains the twelveth day of the month, but production is subsequently resumed, the output data will bear a weak relationship with the labor input data. The problem will be more serious the smaller is the degree of data unit aggregation. In Bresnaham and Ramey (1994) this was a crucial point since they work with plant level data. I work with 2-digit sectors data and in this case the intermittent production problem is much less relevant since aggregation should wash out microeconomic idiosyncrasies.

Furthermore, in order to sign the direction of the bias caused by the sampling methodology it is necessary to know, for instance, if firms tends to (de)accelerate production at the beginning or at the end of the month to meet monthly production. Or, if there is any regular pattern for the production shutdowns for inventories adjustment. Given that this information is not available, there is no reason to assume that the sampling problem causes bias in any particular direction.

Chapter 2

Nominal Rigidities and Real Wage Cyclicality[1]

2.1 Introduction

Surprisingly, empirical studies of wage cyclicality are not derived from the models they are used to test. As Bils (1985) notes, "Without clear reason...the empirical literature on real wages has evolved largely separately from theory." (p. 668)[2] Most models, however, tacitly impose structure on the relationship between wages and the cyclical variable. In Keynesian models with nominal wage rigidity, the prediction of countercyclical wages is derived from a set of specific economic conditions: the labor demand curve is stable and aggregate demand fluctuates over the business cycle. Real business cycle models also contain assumptions which generate the prediction of procyclical wages: individuals trade off labor and leisure and aggregate supply shocks drive the business cycle. In models where firms face noncompetitive product markets, shocks in aggregate demand generate procyclical wages if the markup varies countercyclically and the labor supply is fixed.

It is important to note that these theories rely on different hypotheses about the

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[1] Joint with Beth Anne Wilson.

[2] In the extensive econometric literature on wage cyclicality almost all tests are based on a real wage equation of the following form: $W_{it} = X_i\beta_1 + X_t\beta_2 + X_{it}\beta_3$, where X_i are individual specific effects, X_t are time specific effects (i.e. the business cycle) and X_{it} are individual effects that vary across time, such as tenure. For instance, Bils (1985) and Solon *et al* (1994), regress the first difference of the logarithm of individual real wages on a constant, a trend, the first difference of the unemployment rate and a vector of individual characteristics that varies across time periods.

curve identified and the type of shocks driving the business cycle in order to generate their results. Given the structure imposed by the models, the common strategy of using the average correlation of employment and real wages as a sufficient statistic to reject macroeconomic theories is problematic. In addition, the well-known sensitivity of estimates of wage cyclicality to time period and deflator points out the difficulty in estimating a "true" measure of the average correlation between employment and real wages.[3] (Abraham and Haltiwanger, 1994)

In order to evaluate the neo-Keynesian macroeconomic model, we focus on the identification of both labor demand and labor supply, rather than on estimating the average correlation of wages and employment. In section 2.2 we use a simple version of a neo-Keynesian model, where nominal wages are rigid.[4] From the model we derive equations for labor demand and labor supply. We highlight the fact that the real wage and other regressors used in the specification of each curve differ substantially from each other. In order to identify movements along the two curves, wages are instrumented with unexpected aggregate demand shocks or with variables that belong to agents' information set when they make their decision to supply labor.[5]

Section 2.3 presents the basic results using quarterly aggregate manufacturing data. Using unexpected aggregate demand shocks as instrument, real product wages are countercyclical. The elasticity of employment with respect to real product wages is significant and equal to -0.89. The OLS estimate is -0.21. To identify labor supply we use the labor demand shifters proposed by the theory (lagged producer prices), and find wages are procyclical. Here, estimates of labor supply elasticity are

[3]Sumner and Silver (1989) and Mocan and Topyan (1993) show that wage cyclicality estimates depend on the time period used. They argue that the time period proxies for the relative strength of supply and demand shocks. In periods when supply shocks are stronger (weaker) than demand shocks, wages are procyclical (countercyclical). Sargent (1978) and Nickell and Symons (1990) find significant wage countercyclicality using real product wages and other variables that belong to a labor demand specification as regressors.

[4]The neo-Keynesian model is of particular interest because it has traditionally failed with respect to its prediction of wage cyclicality.

[5]Other papers have studied the response of wages to specific economic shocks. Mocan and Baytas (1991) and Spencer (1994), for instance, estimate VARs using wages, unemployment and output and often identify shocks using oil and money supply shocks. In general, wages are significantly procyclical in response to supply shocks and slightly countercyclical in response to demand shocks.

significant and equal to 0.792. The results are robust to variations in the measure of labor input, the time period of the estimates, and the degree of aggregation and are compatible with previous results in the labor economics literature.

The power of the restrictions derived from the model to identify both labor demand and labor supply can be interpreted as evidence that nominal rigidities are an important channel of transmission of aggregate demand shocks to the real side of the economy. In this sense, the simple neo-Keynesian model appears to be a powerful paradigm.

Recognizing that aggregate data may not be optimal for estimating labor demand curves, in section 2.4, we use disaggregate 4-digit industry data. Here again we find a significant correlation between wages and employment of about negative 1.0. We use these disaggregated data to test the robustness of our conclusions by weakening the assumption of competitive product markets. In this way we can nest the neo-Keynesian model within the framework of cyclical markup models. Our findings contradicts markup countercyclicality theories which predict greater real product wage procyclicality in response to aggregate demand shocks. However, we cannot reject the hypothesis that markups are slightly procyclical. In any case, our results suggest that the assumption of markup insensitivity to aggregate demand shocks fits the data and that the assumption of labor demand insensitivity to aggregate demand shocks is not unreasonable. A brief summary and concluding remarks are found in section 2.5.

2.2 Equation specification and the selection of instruments

The Keynesian prediction that real wages move counter to the cycle begins with the assumption that aggregate demand shocks drive the business cycle. In this case, firms respond to the shocks by changing employment along their labor demand curve, given that nominal wages are rigid in the short run. Because the labor demand curve is negatively sloped, wages will move countercyclically. Two questions arise in testing such an hypothesis: One, are aggregate demand shocks the driving force of the business cycle, and two, in response to aggregate demand shocks, will wages move countercyclically? By trying to get a measure of the average correlation between real wage and employment, much of the empirical work on wage cyclicality has implicitly focused on the first question. However, the results are commonly viewed as answering the second question. This section focuses on the second question and motivates the econometric tests used to evaluate a neo-Keynesian model.

The formalization of the Keynesian argument is as follows: A representative firm maximizes profits in the short-run given the stock of capital, technology, and the product price. Labor and other intermediate goods are variable factors. There are no labor adjustment costs (we relax this assumption later) but capital adjustment costs exist, allowing us to view the stock of capital as given. In this case, firms maximize:

$$\Pi = Pf\left(\frac{A_i N_i}{K_i}\right) K_i - W_i N_i \tag{2.1}$$

where the technology generates constants returns to scale, $f(.)K_i$ is value-added output, K_i is the stock of capital, A_i represents labor-augmenting technical progress, W_i is the wage paid, N_i is the level of employment, and P is the product price. From this maximization problem we get the labor demand equation,

$$N_i^D = g\left(\frac{W_i}{A_i P}\right) \frac{K_i}{A_i}, g = (f')^{-1} \tag{2.2}$$

Assuming every firm faces the same wage and technology implies that their capital-labor ratios are identical and equal to the aggregate ratio. The aggregate labor demand equation is, therefore,

$$N^D = g\left(\frac{W}{AP}\right) \frac{K}{A}, g = (f')^{-1} \tag{2.3}$$

where $N^D = \sum_i N_i^D$ and $K = \sum_i K_i$. Given A and K, employment will be negatively related to real product wages because $f'' < 0$.

Wages and employment will be negatively related if firms respond to aggregate demand shocks by hiring along the labor demand curve (2.3). Notice that the relevant wage in this case is the "real cost of labor". Furthermore, the stock of capital and measures of technological progress are included in the equation. If the price data used are not value-added prices, but product or gross-output prices, the equation must also include the real price of intermediate goods and raw materials.

Equation (2.4) describes a linear specification for labor demand where we allow for labor adjustment costs. Lags of employment and real product wages capture these costs under the assumption that only real wages are used to form expectations of future real wages.[6] Lower-case letters represent the logarithm of the respective variables.

$$LD: n_t = \alpha_1 + \sum_{i=0}^{l} \alpha_{2i}(w_{t-i} - p_{t-i}) + \sum_{i=1}^{l} \alpha_{3i} n_{t-i} + \alpha_4 p_{ot} + \alpha_5 a_t + \alpha_6 k_t + \epsilon_t \quad (2.4)$$

Here, n_t represents employment; w_t is the nominal wage; p_t is the product price; p_{ot} is the relative price of other inputs; a_t is total factor productivity; k_t is the stock of capital; and l is the number of real wage and employment lags included in the regression.

The next step is to specify aggregate labor supply. Assuming a representative household, we write the labor supply function as,

$$N^S = N^S\left(\frac{W}{P_c^e}, \lambda\right) \quad (2.5)$$

where λ represents the marginal utility of wealth and P_c^e is the expected consumer price. In this case, aggregate demand shocks could shift labor supply through changes in λ, but then aggregate consumption would be countercyclical. We avoid this implausible implication by assuming that nominal wage rigidities, associated with differences in the expected and actual consumer price, play important roles in transmitting aggregate demand shocks to real economic activity. Defining, $P_c = P_c^e e^\eta$ as

[6]See Sargent (1978).

the actual consumer price index we write the labor supply function as

$$N^S = N^S\left(\frac{W}{P_c e^{-\eta}}, \lambda\right) \tag{2.6}$$

Introducing time subscripts, η_t represents unexpected changes in the consumer price level at instant t.

Equation (2.7) presents a linearized version of (2.6). Lagged values of employment are included to capture the correlation of the labor-leisure trade-off across time.[7] Lagged wages are used to account for sluggish responses of labor supply to wage changes. Here, w_t is the hourly wage; p_{ct} is the consumer price index (CPI) and pop_t captures working age population.

$$LS : n_t = \beta_1 + \sum_{i=0}^{j} \beta_{2i}(w_{t-i} - p_{ct-i}) + \sum_{i=1}^{j} \beta_{3i} n_{t-i} + \beta_4 pop + \beta_2 \eta_t \tag{2.7}$$

Now aggregate demand shocks have real effects in the short run if they affect η_t , the unexpected movement in prices. Because wage contracts are based on expected prices, unexpected movements in aggregate demand affect the *ex post* real wage received by workers by perturbing the actual price level. Under the assumption that unexpected shocks in aggregate demand do not affect the position of the labor demand curve, we may use variables that are correlated with these shocks to shift the labor supply curve and identify labor demand.[8] Good candidates for labor supply-shifters are unexpected movements in the current federal funds rate or money growth.

The identification of the labor supply curve is more problematic under this framework. Other authors have found procyclical wages using changes in productivity, energy prices or oil prices to identify the relationship between output and wages.[9] Changes in the price of oil, or of other raw and intermediate inputs, shift the labor demand curve, but would only be good instruments for the estimation of (2.7) if they

[7] See Hansen (1985).

[8] Section 4 discusses theories where the markup is sensitive to exogenous demand shocks. In these cases the labor demand curve would shift when firms face demand shocks and the identification method described above is not valid.

[9] See for example, Mocan and Baytas (1991).

are uncorrelated with unexpected changes in consumer prices, η_t. If this assumption is not correct, supply shocks will also shift labor supply preventing its identification.[10] Because the main concern here is with identifying labor supply, we use a different strategy.

η_t is, by definition, independent of any variable in the information set of individuals at $t-1$. Therefore, variables used by agents in period $t-1$ to predict the consumer price level at t, can be used as instruments for real wages at t. We assume that agents use lagged consumer price levels and productivity to predict future price levels. This is a reasonable assumption but there is still one problem. Consumer prices are not directly included in the labor demand equation. Lags of producer prices, however, are correlated to lags of consumer prices and belong in the labor demand equation. Therefore, we may use lagged producer prices as instrumental variables to estimate the labor supply curve.

2.3 Results using aggregate data

This section presents cyclical coefficients estimated from the labor supply and demand equations. Using the model described above, we find that equation identification leads to striking differences in the estimated correlation between real wage and employment growth: Instrumenting with lagged prices, wages are significantly more procyclical once we use the labor supply specification. When aggregate demand shocks are used as instruments, wages are significantly countercyclical in the labor demand specification.

Two regressions representing labor demand and labor supply are estimated. To estimate labor demand, equation (2.4) is modified. Lacking reliable data for the stock of capital at quarterly frequency, we introduce trend terms in part to capture changes in the capital stock. Both equations are specified in first differences since employment is integrated of order 1. ξ_t, representing other omitted variables in the labor supply

[10] A positive correlation between employment and real wages could still exist if shocks in input prices cause "small" shifts in labor supply and "big" shifts in labor demand. When we identify equation (2.7) using changes in the price of oil and in total factor productivity, the elasticity of employment with respect to real wage is significantly positive. This result corroborates previous findings that supply shocks generate wage procyclicality but cannot be consistently included in our framework.

equation, and ϵ_t are assumed to be i.i.d.. $\Delta\eta_t$, ξ_t and ϵ_t are also assumed to be independent from one another. The equations estimated are:

$$LD : \Delta n_t = \alpha_1 + \sum_{i=0}^{l} \alpha_{2i}\Delta(w_{t-i} - p_{t-i}) + \sum_{i=1}^{l} \alpha_{3i}\Delta n_{t-i} + \alpha_4\Delta p_{ot} + \alpha_5\Delta a_t + \alpha_6 t + \alpha_7 t^2 + \epsilon_t \tag{2.8}$$

$$LS : \Delta n_t = \beta_1 + \sum_{i=0}^{l} \beta_{2i}\Delta(w_{t-i} - p_{ct-i}) + \sum_{i=1}^{l} \beta_{3i}\Delta n_{t-i} + \beta_4\Delta pop + \beta_2\Delta\eta_t + \xi_t \tag{2.9}$$

$\xi_t' = \beta_2\Delta\eta_t + \xi_t$ is the residual term in the labor supply equation. As discussed above, $\sum_{i=0}\alpha_{2i}$ is expected to be negative and $\sum_{i=0}\beta_{2i}$ positive.

The data used to estimate equations (2.8) and (2.9) are quarterly aggregate manufacturing data from 1947:1 to 1992:3. Two measures of nominal wages are used: total compensation per employee, including wages and salaries of employees and employer contribution to social insurance and private pension plans; and average hourly earnings which includes overtime. The compensation measure better captures labor costs and average hourly earnings better represents worker earnings.[11] The nominal wage measures are deflated by the PPI and CPI-U for equations (2.8) and (2.9) respectively. Employment is aggregate manufacturing employment. The price of intermediate inputs divided by the total PPI is used for p_{ot}.[12] a_t is manufacturing total factor productivity. Two measures of working age population are used: the population between 20 and 54 and between 34 and 45. All data are taken from CITIBASE.

Regression results are presented in Table 2.1. Recall that the goal is to see how identification of the wage equation alters estimates of the relationship between wages

[11]Bernheim and Scholz (1993) find evidence that workers without college education do not incorporate their pension benefits into their estimates of total income. Since production workers are not on average college educated, it is fair to assume that average hourly earnings better represents their perception of earnings.

[12]The estimates in the labor demand specification are very robust to changes in the price index for raw and intermediate inputs. The inclusion of an oil price dummy or a variable representing the actual real oil price does not alter the results.

and employment. The table presents the sum of the wage and lagged wage coefficients and the F-test that this sum is zero.[13] The first two sections of results are from estimates using the total compensation per employee measure (comp); the second two sections use the average hourly earnings variable (ahe).

Column (1) presents the OLS results. Varying the specification has noticeable effects. Using real compensation, the labor demand specification yields a far more significant countercyclical coefficient on wages. Switching the wage measure to average hourly earnings (ahe) generates stronger results for labor supply estimates. The coefficient changes from approximately zero to a positive and significant 0.541. We include the χ^2 statistic of the test for the existence of serial correlation of order one in the residuals, proposed by Godfrey (1978). The tables in the Appendix present additional statistics for tests of serial correlation of higher order. We did not detect any relevant evidence of serial correlation in the residuals.

The OLS results are still misspecified and in order to be truly confident in the estimates, instruments are needed to address the simultaneity problem of the basic equations. To capture demand shocks and, thus, identify labor demand, current and lagged unexpected changes in the 6-month real federal funds rate are used as the instrument for wages.[14] Lagged values of producer prices, real consumption wages and productivity growth are used as instruments for the contemporaneous real consumption wage in order to identify labor supply. Lags of the other independent variables are used as additional instruments.

Column (2) contains coefficients estimated using the instruments. For labor de-

[13]Tables in the Appendix contain complete regression results. Coefficients on other variables of the demand equation enter with expected signs. Increasing the price of other inputs negatively affects employment. Improved productivity has a positive effect. Population has little influence on labor supply, probably being well captured by the trend. The residuals do not present any sign of serial correlation.

[14]The unexpected real interest rate series is obtained by, first, estimating the one-step-ahead forecast of the following equation:

$$r_t = d_{0t} + d_{1t}r_{t-1} + d_{2t}r_{t-2} + d_{3t}r_{t-3} + d_{4t}pol_t + \nu_t \qquad (2.10)$$

where *pol* is a political business cycle dummy that is 1 in the two years prior to an election and the interest rate is deflated by the GDP implicit deflator. Second, by taking the difference between the observed r_t and the forecasted r_t.

Table 2.1: Results using aggregate manufacturing data from 1947:1 to 1991:4

Specif.	Dep.var.	ln(Employment)		ln(Hours)	
	Est. method	(1) OLS	(2) IV	(3) OLS	(4) IV
LD^a	Δw_p^{comp}	−0.214	−0.894	−0.244	-0.947
	F-stat	4.490*	6.910**	3.260	4.820*
	R^2	0.57		0.527	
	$\chi^2(1)^c$	0.898		0.604	
	Deg. of Freedom	182	140	172	140
LS^b	Δw_c^{comp}	−0.239	−0.411	−0.308	−0.495
	F-stat	1.320	0.520	1.210	0.440
	R^2	0.396		0.333	
	$\chi^2(1)^c$	0.207		0.360	
	Deg. of Freedom	173	172	173	172
LD^a	Δw_p^{ahe}	0.060	−1.026	0.104	−1.094
	F-stat	0.340	3.290	0.560	2.410
	R^2	0.530		0.494	
	$\chi^2(1)^c$	2.632		0.783	
	Deg. of Freedom	180	140	172	140
LS^b	Δw_c^{ahe}	0.541	0.792	0.761	1051
	F-stat	8.110**	4.410*	8.470**	4.020*
	R^2	0.530		0.449	
	$\chi^2(1)^c$	0.586		0.643	
	Deg. of Freedom	173	172	173	172

[a] Demand shifter used: contemporaneous and lagged unexpected changes in the 6-month federal funds rate and lagged independent variables.
[b] Supply shifter used: lagged price growth, productivity, and independent variables.
[c] χ^2 statistics for the test of serial correlation of order one in the residuals.
* 5 percent significance level.
** 1 percent significance level.

mand specifications, instrumenting increases the size of the coefficient dramatically. The effect of labor supply instruments is also large – when the average hourly earnings measure of wages is used, the coefficient increases after instrumenting, from 0.541 to 0.791. The exception to this pattern is the supply specification with compensation as the wage measure. In this case, neither the OLS nor the IV coefficients are significantly different from zero.

The most significant negative coefficient is found when compensation is used in the labor demand equation. The strongest and most significant positive coefficients are found when average hourly earnings are used in the labor supply equation. Thus confirming the idea that compensation better captures product wages and average hourly earnings better represents consumption wages. The results are also in keeping with those in the literature. (Nickell and Symons, 1990; Kennan, 1988)

For these regressions, one lag of both wages and employment are included as independent variables. The results are robust to changes in the lag lengths of regressors and of variables in the instrument set. In addition, the level specification yields very similar coefficients. Columns 3 and 4 of Table 2.1 contain results from similar estimations using the change in total hours as the dependent variable. The elasticity of total hours of work demanded by firms with respect to changes in hourly real product wage is -0.947.[15] The elasticity of total hours of work supplied with respect to the hourly consumption wage is 1.051. The coefficient estimates are very similar to the estimates presented in columns (1) and (2).

Most of the previous estimates for the absolute value of the elasticity of labor demand with respect to real wages lie in the interval $[0.15, 0.75]$.[16] Our IV estimates using both definitions of labor input, employment and hours, are not far away from the upper limit of this interval. The slightly larger estimates we obtain can be explained by the use of instrumentation. The majority of previous elasticity estimations are

[15]We can also calculate "long-run" elasticities of labor demand, as well as for labor supply, using the coefficient estimates of the lagged dependent variable. The long-run elasticity of demand for total hours would be -1.67. We do not focus on the distinction between short and long-run elasticities here because the general direction of our results is the same in both cases.

[16]This interval is calculated using the numbers reported in a comprehensive survey of the empirical labor demand literature presented in Hamermesh (1993).

based on identifying assumptions that avoid the direct use of instruments.[17] Such estimates can be viewed as lower bounds for the actual value of the elasticity of labor demand. The large range of estimates for aggregate labor supply elasticities forbids meaningful comparison of our results with previous estimates.[18]

As mentioned earlier, traditional estimates of the average correlation of wages and employment are sensitive to time period. To confirm that identification ameliorated this problem we reestimated each of the 4 specifications using interactive time dummies to capture differences in the cyclical coefficients for different time periods. The three time periods we selected were 1966-1982, the period used in Bils (1985); 1968-1988, the period of Solon, Barsky and Parker (1993), and the 1959-1972 period of Sargent (1978). We used only one time dummy per regression and of the 12 different regressions (not reported here) only 1 had a significant interactive dummy.

In sum, the IV results suggest that when the economy faces aggregate demand shocks, real product wages are countercyclical, as predicted by the neo-Keynesian model. In other words, nominal wage rigidity seems to be an important channel of transmission of aggregate demand shocks to employment and real wages. In addition, we find that the same model generates restrictions powerful enough to identify the labor supply curve.

On the other hand, the OLS results point out the importance of specification for estimating wage cyclicality. When estimating the average correlation between employment and real wages (estimation without identification of economic shocks), a choice must be made as to time period, wage measure, and deflator. Depending on the wage measure and the deflators used one goes in the direction of identifying labor demand or labor supply. Using the CPI, excluding the price of other inputs and technology, and estimating over periods dominated by supply shocks, as in much of the recent wage cyclicality literature, the results are implicitly biased toward identifying labor supply.[19]

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[17] See Hamermesh (1993), tables in chapter 3 and chapter 7.

[18] See the survey on previous estimates of labor supply elasticities in Killingsworth (1983), chapters 3, 4 and 5.

[19] Nickell and Symons (1990) suggested that just the use of different definitions for the real wage

2.4 Labor demand estimates using disaggregated data

2.4.1 Benchmark results

For Table 2.1, quarterly aggregate manufacturing data are used. However, cyclical variation in the industry composition of this data is known to affect estimates of wage cyclicality. (Chirinko, 1981, and Bils and McLaughlin, 1992) While aggregate data are appropriate for estimating labor supply, identifying labor demand may call for more disaggregated data. In moving from an aggregate framework to an industry one, we can control for industry characteristics that may affect the aggregate results obtained in the previous section. In addition, the restriction that the labor demand curve does not shift when firms face a product demand shock can be checked more directly, thus providing a robustness test for our identifying assumption in previous sections.

The data used in this section are from the Gray productivity database – an extensive dataset with annual data on 450 manufacturing industries from 1958 to 1989.[20] We use total employment (production and non-production workers) and hours of work of production employees as measures of industries' labor input. Real product wages are calculated dividing total wage bill by the number of hired workers and deflating by the sectoral producer price, when total employment is used as dependent variable. An hourly definition for the real product wage is used when hours of work is the dependent variable. We also use information on industries' capital stock, total factor

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included in the labor supply or in the labor demand specification, can represent an important step toward the identification of both curves. Assuming that the only difference between labor demand and labor supply is the relevant price index to deflate wages, we may write both equations as: $LD : n = -\alpha w + \epsilon$, $LS : n = \beta(w + \theta) + \eta$, where ϵ and η are i.i.d. , w represents real product wages and θ is the differential between real product wages and real consumption wages. Assume that ϵ, θ and η are independent.

The plim of the OLS estimate of β can be written as, $\beta + \frac{(\alpha+\beta)\sigma_\eta^2}{(\beta^2\sigma_\theta^2+\sigma_\eta^2+\sigma_\epsilon^2)}$. Therefore, the higher the variance of the differential between producer and consumer prices, the closer the estimates will be to the labor supply elasticity, i.e. the "more procyclical" wages will be. The OLS estimations of these simple specifications, using the data described in this section are $\alpha_{OLS} = -0.358$ and $\beta_{OLS} = 0.748$, both significantly different from zero.

[20]See Gray (1989) for a detailed description of this database.

Table 2.2: Results using disaggregate industry-level data from 1959 to 1989

Dep. variable	Δln(employment)		Δln(hours)	
	(1)	(2)	(3)	(4)
Est. method	OLS	IV	OLS	IV
Δw_p	-0.52^{**}	-0.93^{**}	-0.65^{**}	-1.34^{**}
	(-36.87)	(-15.24)	(-47.71)	(-20.22)
R^2	0.22		0.26	
Deg. of Freedom	13,937	13,489	13,489	13,489

Demand shifter used: contemporaneous and lagged unexpected changes in the 6-month federal funds rate, lagged independent variables. 450 sectors. Each sector has annual data for the period 1960-1989. Columns (1) and (2): Real wage: Total wage bill divided by the number of employees, deflated by sectoral producer price. Columns (3) and (4): Real wage: Production workers wage bill divided by the number of production work hours, deflated by the sectoral producer price.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

productivity, and the price of other inputs. The results are insensitive to the use of the number of production workers as dependent variable. Contemporaneous and lagged unexpected changes in the real federal funds rate and lags of the other regressors are used as instruments. The final specification is presented in (2.11), where i is a sectoral index.

$$LD : \Delta n_{it} = \alpha_1 + \alpha_2 \Delta w_{pit} + \alpha_3 \Delta n_{it-1} + \alpha_4 \Delta p_{oit} + \alpha_5 \Delta a_{it} + \alpha_6 t + \alpha_7 t^2 + \alpha_8 \Delta k_{it} + \epsilon_{it} \tag{2.11}$$

k_{it} represents the sectoral stock of capital series. The fixed effects are factored out by taking first differences. The specification for the labor demand curve used here does not include lags of real product wages, since we are using annual data. Initially, the coefficients of each variable are held constant across sectors. In the next subsection we allow these coefficients to vary with sectoral characteristics.

Initial OLS regressions yield the, now, familiar negative coefficient on wages. The IV results provide confirmation that in response to exogenous increases in demand, wages and employment move in opposite directions. Columns (3) and (4) of Table 2.2 show that the results are insensitive to the use of total hours of work as the dependent variable.

2.4.2 Identification of labor demand and the effect of market power

Until this point our identification strategy has relied on the fact that labor demand is invariant to product demand shocks. If labor demand shifts, this strategy is not appropriate. Although we find a high negative correlation between employment and real product wages, we may not be capturing movements along the labor demand curve (as the model developed in section 2.2 predicts), but some combination of shifts in both the labor demand and labor supply curves. A possible link between aggregate demand shocks and shifts in sectoral labor demand comes from theories which predict that markups are sensitive to demand shocks.

This section discusses the interpretation of our earlier estimates if the economy is better represented by a cyclical markup model. In general, in such models, the degree of markup cyclicality varies with industry characteristics. Analyzing the sensitivity of the real product wage/employment elasticity to sectoral characteristics provides a test to distinguish between the fixed and flexible markup theories, where the fixed markup model is a more general case of the neo-Keynesian model presented before.

Three different models are examined: the fixed markup model; the customer market model; and the collusive market model. The relationship between markup and wages in the fixed markup case can be shown by the first-order condition of a representative firm:

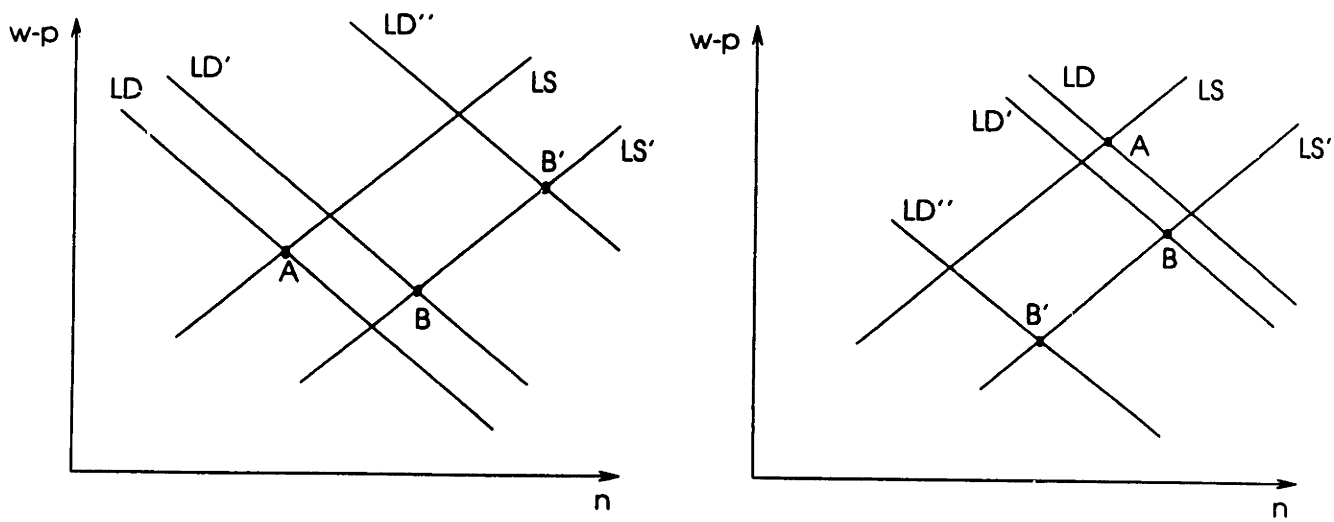
$$F_N(N_{it}, K_{it}, A_{it}) = \mu_{it} w_{it} \tag{2.12}$$

Here $F_N(.)$ represents the marginal product of labor, μ_{it}, the markup, and w_{it}, the real wage. Equation (2.12) is a more general formula than equation (2.2), where it was assumed that $\mu_{it} = 1$ and that the technology generates constant returns to scale. If markups are fixed, we have that $\mu_{it} = \mu_i$, so that the markup depends only on sectoral characteristics. As before, unexpected shifts in aggregate demand cause price variations which are not immediately incorporated into changes in nominal wages. The *ex post* labor supply shifts and the labor demand curve is mapped out. In the fixed markup model, the markup is invariant to market conditions, therefore, unexpected changes in aggregate demand still identify the labor demand curve.

In the next two models, customer and collusive market models, the markup responds to changes in market conditions. In the customer market model of Phelps and Winter (1970), when firms face positive demand shocks, given the future state of demand, they increase the markup to exploit existing customers. The cost of losing market share is outweighed by the benefits of a higher profit margin. This model predicts markup procyclicality. In the collusive model of Rotemberg and Saloner (1986), when firms face a positive demand shock, given the future state of demand, the incentive to deviate from the collusive equilibrium increases and the new equilibrium level for the markup is smaller than before. This model predicts markup countercyclicality.

When the markup is flexible, identifying labor demand becomes problematic. In the case where μ_{it} is a function of demand shocks, changes in demand now result in shifts in as well as movements along the labor demand curve since *ex post* labor supply shifts. We can no longer give a structural interpretation to our coefficients, aside from their being the correlation between wages and employment in response to demand shocks.

Recognizing that these models of markup behavior have different implications for the interpretation of our earlier results, what can we now conclude? We estimate a significantly negative correlation of real wage growth and employment growth once we identify the real product wage with demand shocks. With this negative correlation, if markups are fixed, we can interpret our results as identifying a labor demand curve. If markups are flexible, the finding real product wage countercyclicality suggests that relatively small shifts in the labor demand curve occur in response to industry demand shocks (i.e. the markup is relatively insensitive to changes in sectoral demand). In this situation, our estimates either under- or overestimate the slope of the labor demand



Collusion Model

Customer Market Model

Figure 2-1: Markup cyclicality and labor demand shifts

curve.[21]

Figure 2-1 highlights the uncertain sign of the correlation between wage and employment growth when aggregate demand shocks shift both the labor demand and supply curves. In the collusion model, the labor demand and supply curves shift out in response to a positive demand shock. The relative strength of the two shifts determines the correlation of wages and employment. Moving from A to B' leads to a positive correlation between wages and employment while moving from A to B suggests a negative relationship.

The same ambiguity is true in the customer model. In this case, labor demand shifts back in response to a demand shock. If the shift in labor demand is strong relative to the shift in labor supply (A to B'), wages are positively correlated to

[21]We are assuming here that the markup is only sensitive to variations in the state of demand. In other words, $\mu_{it} = \mu(D_t, i)$, where D_t represents the level of aggregate demand. In more general models, markup could be a function of sales if, for instance, the elasticity of the demand for goods is not constant.

employment. The reverse is true if the shift is weak (A to B). Our estimates for the labor demand elasticity will be downward biased in absolute terms in the collusion model (we will be tracing a line passing through points A and B) and upward biased in the customer market model (for the same reason).

It would be useful to distinguish empirically among the various types of markup models in order to establish the direction of the bias in our estimates or to reinforce the identifying assumption that labor demand does not shift when firms face demand shocks. As suggested by previous works, we use variations in industry concentration to test the implications of these models. (Rotemberg and Woodford, 1991)

To establish the link between markup, industry concentration, and wage cyclicality in the fixed markup model we begin by assuming that markups are positively related to industry concentration indexes. Sectors with stronger monopoly power in the goods market (high industry concentration) fix a higher markup over wages, have a flatter labor demand curve and higher (more negative) elasticity of employment with respect to wages.[22] Therefore, in the fixed markup model, if we use the degree of market share concentration at the 4-digit level of aggregation as a measure of firms' market power, we should find sectors with a high degree of concentration having a larger (in absolute value) employment/real product wage elasticity.

In the collusion model, we expect less real product wage countercyclicality, or even real product wage procyclicality in highly concentrated sectors. Firms in sectors with significant product market concentration have more to gain in the short run from undercutting their rivals. Therefore, a shock of the demand for goods will result in a bigger outward shift in the labor demand curve in those sectors. Consequently, real product wages will decrease less in highly concentrated industries (they may in fact increase) than in sectors that are less concentrated. The prediction for the customer market model is less clear since a strong downward shift of labor demand

[22]Totally differentiating (2.12) with respect to N_{it} and w_{it} yields $\frac{dN_{it}}{dw_{it}} = \frac{\mu_i}{F_{NN}} < 0$ and $\epsilon_{it} = \frac{dN_{it}}{dw_{it}}\frac{w_{it}}{N_{it}}$. In order to know how both the inclination and the elasticity of labor demand with respect to real product wages vary with the level of markup we have to totally differentiate both expressions with repect to μ_i. The result depends on the third derivative of the production function with respect to employment (F_{NNN}). If this is not large and positive, both the inclination and the elasticity of labor demand decreases (increases in absolute value) when markup increases.

would imply real wage procyclicality while a small shift would imply more real wage countercyclicality.

To carry out the test between the markup models, we modify our original labor demand specification. We now include an interactive term which captures the effect of concentration on the sectoral elasticity of demand.[23] The cyclical coefficient now has two components: α_{20}, the average elasticity of labor demand in our sample, and α_{21}, the sensitivity of this elasticity with respect to the level of product market concentration. We measure c_i as the difference of industry concentration from the mean and use the across-time average of the Census four-firm concentration index as a measure of C_i.[24]

The first two columns of Table 2.3 contain estimates of α_{20} and α_{21}, controlling only for product market concentration. Column (1) presents the OLS results. Estimates show that wages are countercyclical. The countercyclicality diminishes, however, as the degree of product-market concentration increases. This initial result lends support to flexible markup models. Column (2) presents the instrumental variables estimates. The estimate for the average elasticity of labor demand is now almost three times larger than in the OLS case. In addition, the coefficient for the interactive term becomes negative. [25]

Other sectoral characteristics may be driving this result. Industries with high capital-labor ratios may charge a higher markup over wages in downturns to compensate for the fact that fixed costs comprise a larger share of total costs in these situations. The pricing mechanism of firms in the durable goods sector could differ structurally from the pricing mechanism of firms in the non-durable goods sector (Bils, 1989). Column (3) shows regression coefficients once we control for these two

[23]Formally we linearize the function that relates the sectoral elasticity of labor demand, α_{2i}, to the degree of product market concentration, C_i, around the average degree of concentration, C: $\alpha_{2i} = \alpha_{20} + \alpha_{21} c_i$, where, $c_i = C_i - C$.

[24]This approach maximizes the number of observations in our sample since we would lose over two-thirds of our observations if we considered the time dimension of the data on product market concetration. Furthermore, a sector's rank according to its degree of market concentration is fairly constant across time.

[25]One interactive term between unexpected changes in the federal funds rate and the degree of product market concentration was included in the instrumental variables set.

Table 2.3: Controlling for product market characteristics, industry data (1959-1989)

Dep. Variable	$\Delta \ln$(employment)			$\Delta \ln$(hours)		
	(1)	(2)	(3)	(4)	(5)	(6)
Est. Method	OLS	IV	IV	OLS	IV	IV
Δw	-0.53^{**}	-1.42^{**}	-1.01^{**}	-0.68^{**}	-1.58^{**}	-1.56^{**}
	(-37.24)	(-18.84)	(-10.68)	(-49.96)	(-20.24)	(-14.10)
$\Delta w * c$	0.00^{**}	-0.01^{**}	-0.01^{*}	0.01^{**}	-0.01	-0.01
	(5.32)	(-2.78)	(-1.96)	(14.57)	(-1.33)	(-1.34)
$\Delta w * dur$	—	—	0.56^{**}	—	—	0.75^{**}
			(3.40)			(2.34)
Other sectoral characteristics	NO	NO	YES	NO	NO	YES

Columns (1), (2) and (3): Real wage: Total wage bill divided by the number of employees, deflated by sectoral producer price. Columns (4), (5) and (6): Real wage: Production workers wage bill divided by the number of production work hours, deflated by the sectoral producer price.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

effects.[26]

Following Domowitz et al (1988), an industry is defined as belonging to the durable goods sector if it produces capital goods – for use either by households or firms.[27] To capture industry capital intensity, we used the average across time of the capital-labor ratio. The results in column (3) show that the effect of product market concentration is still negative and statistically significant when we control for the industry type.

The complete table of results is in the Appendix. The coefficient for the interactive term between the durable goods dummy and the change in the real product wage is 0.56 and significantly different from zero. This provides evidence that markups

[26]Multiplicative terms between changes in wages and every sectoral characteristic, as well as, multiple interactive terms are introduced. We included also the same interactive term using the aggregate demand shock variable instead of the real wage variable in the instrument set.

[27]With few exceptions, the set of durable goods includes the following 2-digit sectors: 25 (furniture), 35 (machinery except electrical machinery), 36 (electronic equipment), 37 (transportation equipment), and 38 (instruments and related products).

are more sensitive to aggregate demand shocks in durable goods industries than in non-durable goods industries although wages are still countercyclical (employment-real product wage elasticity in the durable goods sector is -0.451). This is consistent with the results in Bils (1989). He provides some direct evidence for higher markup cyclicality in the durable goods sector. Unfortunately, the indirect methodology provided here does not allow us to measure the direction of this cyclicality.

By finding a negative effect of increasing concentration on wage cyclicality, we are able to reject the collusion model. We can conclude that the labor demand curve is fairly insensitive to variations in aggregate demand seems to fit the data. However, this result is consistent with both weak markup procyclicality and fixed markups.

2.5 Conclusion

We began this chapter by questioning the practice of distinguishing among macroeconomic theories using estimates of wage cyclicality derived from non-identified wage equations. Traditional estimates of the average correlation of employment and wages are very sensitive to the choice of deflator, nominal wage measure, and time period. This sensitivity is interpretable within the neo-Keynesian framework: The choice of these variables represents an implicit move toward identification of the labor supply or the labor demand curve.

In general, theoretical models which predict a correlation between real wages and employment do so by specifying either a labor demand or a labor supply curve and assuming specific types of aggregate shocks. In order to better evaluate one particular theory, the neo- Keynesian model, we test its predictions for the correlation of wages and employment by deriving our empirical tests directly from specifications of labor demand and supply. We then identify movements along these curves through the use of instruments derived from the theory.

Results using aggregate data show that the real product wage is countercyclical in response to aggregate demand shocks. This result is consistent with the neo-Keynesian model where unexpected demand shocks shift the labor supply curve due to nominal wage rigidities and map out labor demand. Procyclical wages are estimated when the real consumption wage is used and the equation is identified using instruments that shift labor demand.

To test the robustness of our estimates we use disaggregated industry level data. We find stronger evidence of a negative correlation between real wage and employment growth. Markup cyclicality theories predict that the labor demand curve is sensitive to aggregate demand shocks. This sensitivity may vary with industry characteristics. Therefore, we use these disaggregated data to test the robustness of our hypothesis concerning the stability of the labor demand curve to aggregate demand shocks.

We relax the assumption that markets are competitive and nest the predictions of the neo-Keynesian (or fixed markup model) within a larger set of markup models. The existence of countercyclical wages and additional evidence of a negative effect of concentration on estimates of wage cyclicality contradicts one of the basic predictions of the collusive behavior model.

However, we are unable to truly determine whether markups are fixed or flexible by looking at the interaction of market concentration and wage behavior since our results are consistent with weak markup procyclicality. In addition, industries in the durable goods sectors show significantly smaller real product wage countercyclicality. Although this result provides evidence that markups are more cyclical in durable goods industries, these sectors are not driving the estimates for the aggregate employment-real product wages elasticity. The estimate of the average elasticity for the whole sample is nearly identical to the average elasticity obtained for the industries in the non-durable goods sector.

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2.7 Appendix: Tables of results

Table 2.4: Detailed regressions from Table 2.1

Variable	Δw_p^{comp} OLS	Δw_p^{comp} IV	Δw_p^{ahe} OLS	Δw_p^{ahe} IV
Δw	-0.301^{**}	-1.336^{**}	0.033	-1.598^{*}
	(-3.25)	(-2.81)	(0.30)	(-1.84)
Δw_{-1}	0.087	0.470^{**}	0.027	0.571
	(1.06)	(2.38)	(0.30)	(1.64)
Δn_{-1}	0.592^{**}	0.516^{**}	0.641^{**}	0.498^{**}
	(10.92)	(5.41)	(11.87)	(3.57)
Δp_o	-0.021	-0.092^{*}	0.003	-0.123
	(-1.55)	(-1.66)	(0.20)	(-1.33)
Δa	0.682^{**}	0.913^{**}	0.677^{**}	1.189^{**}
	(8.44)	(4.84)	(8.01)	(4.33)
t	0.000	-0.000	0.000	0.000
	(0.78)	(-0.23)	(1.06)	(0.03)
t2	-0.000	0.000	-0.000	0.000
	(-0.66)	(0.28)	(-1.02)	(0.02)
constant	-0.005	0.003	-0.007^{**}	-0.002
	(-1.51)	(0.30)	(-2.35)	(-0.20)
Sum wage coeff.	-0.214^{*}	-0.894^{**}	0.060	-1.026
F-stat.	4.490	6.910	0.340	3.290
R^2	0.57		0.53	
Ser.corr. tests				
$\chi^2(1)$	0.898		2.632	
$\chi^2(2)$	2.155		3.322	
$\chi^2(3)$	2.428		3.561	
Deg. of Freedom	182	140	180	140

Labor demand specifications. Dependent variable: Δ ln(employment).
Demand shifter used: contemporaneous and lagged unexpected changes in the 6-month federal funds rate and lagged independent variables.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

Table 2.5: Detailed regressions from Table 2.1 (cont.)

Variable	Δw_c^{comp} OLS	Δw_c^{comp} IV	Δw_c^{ahe} OLS	Δw_c^{ahe} IV
Δw	-0.048	-0.235	0.946**	1.225**
	(-0.33)	(-0.46)	(6.98)	(3.05)
Δw_{-1}	-0.192	-0.176	−0.404**	−0.433**
	(-1.19)	(-1.15)	(-2.67)	(-2.72)
Δn_{-1}	0.715**	0.703**	0.798**	0.803**
	(9.57)	(8.54)	(10.90)	(10.99)
Δn_{-2}	−0.214**	−0.210**	−0.229**	−0.220**
	(-2.87)	(-2.80)	(-3.34)	(-3.21)
t	0.000	0.000	0.000	0.000
	(0.10)	(0.05)	(0.77)	(1.40)
t^2	-0.000	-0.000	-0.000	-0.000
	(-0.44)	(-0.49)	(-0.45)	(-0.87)
constant	0.002	0.003	-0.005	−0.009*
	(0.55)	(0.46)	(-1.39)	(-1.90)
Sum wage coeff.	-0.239	-0.411	0.541**	0.792**
F-stat.	1.320	0.520	8.110	4.410
R^2	0.396		0.530	
Ser.corr. tests				
$\chi^2(1)$	0.207		0.586	
$\chi^2(2)$	0.807		2.527	
$\chi^2(3)$	2.988		2.395	
Deg. of Freedom	173	172	173	172

Labor Supply specifications. Dependent variable: Δ ln(employment).
Supply shifter used: lagged price growth, productivity, and independent variables.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

Table 2.6: Detailed regressions from Table 2.1 (cont.)

Variable	Δw_p^{comp} OLS	Δw_p^{comp} IV	Δw_p^{ahe} OLS	Δw_p^{ahe} IV
Δw	-0.438^{**}	-1.544^{**}	0.024	-1.780
	(-3.52)	(-2.48)	(0.16)	(-1.63)
Δw_{-1}	0.194	0.597^{**}	0.080	0.686
	(1.76)	(2.35)	(0.65)	(1.55)
Δh_{-1}	0.513^{**}	0.434^{**}	0.555^{**}	0.408^{**}
	(9.09)	(4.88)	(9.80)	(3.14)
Δp_o	-0.028	-0.114^{*}	0.004	-0.148
	(-1.54)	(-1.64)	(0.23)	(-1.28)
Δa	0.877^{**}	1.207^{**}	0.872^{**}	1.421^{**}
	(8.08)	(5.16)	(7.62)	(4.38)
t	0.000	-0.000	0.000	0.000
	(0.82)	(-0.14)	(1.09)	(0.07)
t2	-0.000	0.000	-0.000	-0.000
	(-0.69)	(0.14)	(-1.04)	(-0.06)
constant	-0.007	0.001	-0.010^{**}	-0.004
	(-1.58)	(0.10)	(-2.36)	(-0.31)
Sum wage coeff.	-0.244	-0.947^{**}	0.104	-1.094
F-stat.	3.260	4.820	0.560	2.41
R^2	0.527		0.494	
Ser.corr. tests				
$\chi^2(1)$	0.604		0.783	
$\chi^2(2)$	1.255		1.243	
$\chi^2(3)$	2.483		1.602	
Deg. of Freedom	172	140	172	140

Labor demand specifications. Dependent variable: Δ ln(hours of work).
Demand shifter used: contemporaneous and lagged unexpected changes in the 6-month federal funds rate and lagged independent variables.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

Table 2.7: Detailed regressions from Table 2.1 (cont.)

Variable	Δw_c^{comp} OLS	Δw_c^{comp} IV	Δw_c^{ahe} OLS	Δw_c^{ahe} IV
Δw	-0.201	-0.431	1.134**	1.457**
	(-1.03)	(-0.65)	(6.06)	(2.64)
Δw_{-1}	-0.106	-0.064	−0.373*	−0.407*
	(-0.55)	(-0.31)	(-1.81)	(-1.92)
Δh_{-1}	0.642**	0.639**	0.684**	0.692**
	(8.58)	(8.04)	(9.22)	(9.47)
Δh_{-2}	−0.195**	−0.197**	−0.190**	−0.186**
	(-2.60)	(-2.60)	(-2.74)	(-2.71)
t	-0.000	0.000	0.000	0.000
	(-0.03)	(0.05)	(0.66)	(1.33)
t^2	-0.000	-0.000	-0.000	-0.000
	(-0.27)	(-0.42)	(-0.31)	(-0.79)
constant	0.003	0.004	-0.006	−0.011*
	(0.61)	(0.41)	(-1.33)	(-1.83)
Sum wage coeff.	-0.308	-0.495	0.761**	1.051*
F-stat.	1.210	0.440	8.470	4.020
R^2	0.333		0.449	
Ser.corr. tests				
$\chi^2(1)$	0.360		0.643	
$\chi^2(2)$	2.669		6.656*	
$\chi^2(3)$	4.475		6.589	
Deg. of Freedom	173	172	173	172

Labor Supply specifications. Dependent variable: Δ ln(hours of work).
Supply shifter used: lagged price growth, productivity, and independent variables.
t-statistics in parentheses.
*** 5 percent significance level.**
**** 1 percent significance level.**

Table 2.8: Detailed regressions from Table 2.2

Dep. variable	Δ ln(employment)		Δ ln(hours)	
	(1)	(2)	(3)	(4)
Variable	OLS	IV	OLS	IV
Δw	-0.52^{**}	-0.93^{**}	-0.65^{**}	-1.34^{**}
	(-36.87)	(-15.24)	(-47.71)	(-20.25)
Δn_{-1}	0.01^{*}	0.05^{**}	0.03^{**}	0.03^{**}
	(2.02)	(5.98)	(3.82)	(3.76)
Δk	0.31^{**}	0.34^{**}	0.34^{**}	0.44^{**}
	(25.10)	(10.40)	(20.20)	(11.57)
Δp_o	-0.27^{**}	-0.29^{**}	-0.29^{**}	-0.35^{**}
	(-11.57)	(-3.98)	(-11.26)	(-3.61)
Δtfp	0.90^{**}	1.38^{**}	1.07^{**}	1.91^{**}
	(56.46)	(15.73)	(59.02)	(13.81)
t	-0.01^{**}	-0.01^{**}	-0.01^{**}	-0.01^{**}
	(-4.81)	(-4.73)	(-4.63)	(-3.99)
t_2	0.00^{**}	0.00^{**}	0.00^{**}	0.00^{**}
	(4.25)	(4.31)	(4.20)	(3.51)
constant	0.32^{**}	0.39^{**}	0.37^{**}	0.40^{**}
	(5.25)	(5.08)	(4.93)	(4.36)
R^2	0.22		0.26	
Deg. of freedom	13937	13489	13489	13489

Columns (1) and (2): Real wage: Total wage bill divided by the number of employees, deflated by sectoral producer price. Columns (3) and (4): Real wage: Production workers wage bill divided by the number of production work hours, deflated by the sectoral producer price.
t-statistics in parentheses.
* 5 percent significance level.
** 1 percent significance level.

Table 2.9: Detailed regressions from Table 2.3

Dep. variable	$\Delta\ln$(employment)			$\Delta\ln$(hours)		
Variable	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
Δw	-0.532^{**}	-1.424^{**}	-1.007^{**}	-0.684^{**}	-1.582^{**}	-1.556^{**}
	(-37.26)	(-18.83)	(-10.67)	(-49.95)	(-20.24)	(-14.10)
$\Delta w * c$	0.003^{**}	-0.007^{**}	-0.006^{*}	0.007^{**}	-0.006	-0.006
	(5.32)	(-2.77)	(-1.96)	(14.56)	(-1.33)	(-1.34)
$\Delta w * dur$	—	—	0.556^{**}	—	—	0.751^{**}
			(3.40)			(2.34)
$\Delta w * kl$	—	—	-0.002^{*}	—	—	0.000
			(-2.29)			(0.21)
$\Delta w * c * dur$	—	—	-0.006	—	—	-0.009
			(-1.06)			(-0.58)
$\Delta w * c * kl$	—	—	-0.000	—	—	-0.004
			(-0.40)			(-0.17)
$\Delta w * dur * kl$	—	—	-0.026^{**}	—	—	0.000
			(-2.45)			(0.53)
$\Delta w * c * kl * dur$	—	—	0.000	—	—	0.001
			(1.48)			(1.03)
Δh_{-1}	—	—	—	0.028^{**}	0.020^{*}	0.037^{**}
				(3.73)	(1.88)	(3.89)
Δn_{-1}	0.006^{*}	0.009	0.059^{**}	—	—	—
	(2.06)	(0.85)	(6.27)	—	—	—
Δk	0.309^{**}	0.230^{**}	0.287^{**}	0.337^{**}	0.115^{*}	0.394^{**}
	(25.07)	(5.89)	(7.37)	(20.40)	(2.29)	(8.84)
Δp_o	-0.281^{**}	1.009^{**}	0.202	-0.310^{**}	1.550^{**}	-0.411
	(-12.03)	(9.06)	(0.90)	(-12.15)	(9.79)	(-1.35)
Δtfp	0.904^{**}	0.468^{**}	1.119^{**}	1.090^{**}	0.003	1.641^{**}
	(56.63)	(3.94)	(9.50)	(60.33)	(0.01)	(12.37)
t	-0.008^{**}	-0.026^{**}	-0.010^{**}	-0.010^{**}	-0.026^{**}	-0.010^{**}
	(-4.82)	(-9.71)	(-4.64)	(-4.88)	(-8.45)	(-3.36)
t^2	0.000^{**}	0.000^{**}	0.000^{**}	0.000^{**}	0.000^{**}	0.000^{**}
	(4.271)	(9.245)	(4.24)	(4.44)	(7.87)	(2.90)
constant	0.319^{**}	1.003^{**}	0.416^{**}	0.382^{**}	1.052^{**}	0.397^{**}
	(5.27)	(10.17)	(4.97)	(5.19)	(9.01)	(3.78)
R^2	0.223			0.275		
Deg. of freedom	13936	13488	13482	13488	13488	13482

Columns (1), (2) and (3): Real wage: Total wage bill divided by the number of employees, deflated by sectoral producer price. Columns (4), (5) and (6): Real wage: Production workers wage bill divided by the number of production work hours, deflated by the sectoral producer price.
t-statistics in parentheses.

* 5 percent significance level.

** 1 percent significance level.

Chapter 3

The Role of Profits in Wage Determination: Evidence from US Manufacturing[1]

3.1 Introduction

One of the main aims of theoretical work on wage formation is to understand why wages do not clear the market for labor. Many of the theories proposed to explain this phenomenon imply a positive correlation between profits and wages. While empirical evidence on inter-industry wage differentials suggests their structure may be related to profitability, direct tests of the effect of profits on wages in the US economy have found very small estimates. The lack of direct evidence casts doubt on the relevance of profits in wage determination. This chapter provides strong new direct evidence that profit-sharing is an important part of wage determination not only in highly unionized sectors, but in the entire US manufacturing sector.

Previous studies of the US economy have failed to overcome the endogeneity of profits-per-worker in a real wage equation because they lacked appropriate instruments. In the next section, we show that basic bargaining models provide a justification for the assumption that the profit-sharing parameter can be identified with instruments which shift demand for goods. We use information from the input-output table to create measures of demand for 63 4-digit sectors using the methods of Shea

[1] Joint with Stacey Tevlin.

(1993a). The I.V. estimates show that profit sharing is a relevant and widespread phenomenon in the American economy.

The positive correlation between profits-per-worker and wages is predicted by several theories. Efficiency-wage theories emphasize the unprofitability of wage cuts due to their effect on productivity. The fall in productivity may be due to costly worker monitoring (Shapiro and Stiglitz (1984)), or labor turnover costs (Salop (1979)). Akerlof and Yellen (1988) emphasize sociological and psychological reasons for wage stickiness based on the idea of fairness. In their model, firms pay higher wages to their workers when times are good. Thus, efficiency-wage arguments can explain real wage rigidity, wage differentials (since monitoring costs may differ across industries), and a positive relationship between firm profitability and the real wage.

Insider-outsider theories also predict a positive relationship between profits and wages. These models explain insider power by their ability to be uncooperative with new employees, causing adverse effects on overall productivity, and by the fact that the cost of substituting workers increases with the size of the workforce. The larger the rents of a firm, the larger the rent-extraction. See Lindbeck and Snower (1987) for a collection of papers in this tradition. The fundamentals of these models give a rationale for the existence of unions that would be the institutional counterpart of insider power.

Some theories explain wage stickiness as insurance against bad times given by firms to workers who are more risk-averse (the implicit contract models of Azariadis (1975) and Baily (1974)). In these theories, the derivative of wage with respect to profit is positive and equal to the ratio between the relative risk aversion of firms and workers. As long as firms are not risk neutral (as assumed in the original papers), a positive rent-sharing parameter is predicted.[2]

The arguments described above generate a testable implication of the competitive approach to the labor market. If the labor market were truly competitive, insider factors (like firm profitability) would not be important for the determination of the

[2]See Blanchflower *et al* (1992).

real wage paid to a worker.[3] The wage would be equal to the alternative wage. A series of studies using American, British and Canadian data, test the relevance of firm specific variables in an equation for real wage determination when controlling for alternative wage measures. In general, the null hypothesis of joint significance of firms' insider variables cannot be rejected. This conclusion casts doubt on the relevance of the competitive labor market approach.[4]

The problem with the above approach is that the results are not robust to alternative specifications. Each paper includes a set of insider variables but it is not clear what the interpretation for each coefficient is. This chapter follows a different approach. We regress real wages on profits-per-worker and the alternative wage.[5] Previous studies that follow this approach find that the profit-sharing coefficient is positive and significantly different from zero.[6] However, these results find, in general, that the elasticity of real wages with respect to firms' profits is fairly small. Sanfey (1992), estimates an elasticity of wages with respect to profits-per-worker for the American economy of .05, while Blanchflower *et al* (1992), estimate elasticities between .02 and .04. Therefore, although the profit-sharing parameter is significantly different from zero, its size suggests that the competitive labor market paradigm may not be far from the truth. Studies that use data for other countries tend to find similar results. This approach yields a robust result and offers a useful benchmark.

The general problem with these results is that they do not have good instruments

[3]Nickell and Wadwhani (1990) and Nickell and Kong (1988) call "insider variables" variables like firms' monopoly power, workers' bargaining power and technology. The unemployment rate, the average industrial wages and the unemployment insurance benefits would be examples of "outsider variables".

[4]Dickens and Katz (1987) and Layard *et al* (1991) describe these results in detail. Blanchflower *et al* (1992) stress the fact that a model with mobility costs can also generate a positive relationship between profits and wages. In this type of model, short-run wage levels could respond to profit movements, but long-run wage levels would not. When they include lags of the profitability measures in their wage equations, the sum of their coefficients is still positive and this alternative explanation is rejected.

[5]Some of the variables we choose not to include separately (e.g. technology, demand, and market power) are summarized by profits-per-worker, others (e.g. unionization) are part of the rent-sharing parameter.

[6]See Abowd and Lemieux (1993), Blanchflower *et al* (1992), Caruth and Oswald (1990), Christofides and Oswald (1992), Currie and McConnell (1992), Denny and Machin (1991), Hildreth and Oswald (1993) and Nickell and Wadhani (1990).

to identify the profit-sharing parameter. The simultaneity between wages and profits-per-worker generates inconsistent estimates of the wage elasticity with respect to profits. Abowd and Lemieux (1993) estimate a higher elasticity for Canada (0.195) using import and export prices as instrumental variables. They argue that external prices are good instruments because they represent exogenous shocks to product market conditions due to the fact that Canada is a small open economy. Although their work yields evidence against the competitive paradigm for the *unionized* fraction of the Canadian labor market there are two reasons to believe that the US labor market is a more interesting case. First, there is a popular belief that the US labor market is very close to the competitive labor market paradigm. Second, their results are less surprising because they use data from union contracts while the data we use represents the entire US manufacturing sector.

The main difference between our study and previous studies is the empirical strategy followed here. As the next section will show, demand shocks can be used to identify the profit-sharing parameter under plausible assumptions. We solve the simultaneity problem between wages and profits-per-worker using information from the input-output table to select good demand-shifters for some 4-digit sectors of American manufacturing. The methodology is briefly described in the body of the text.[7] The sample used is representative of the whole US manufacturing sector.[8] Our OLS estimates generate an elasticity of 0.05 which matches previous results for the American manufacturing sector. However, using the I.V. procedure, we estimate the elasticity of real wages with respect to profits-per-worker at around 0.33. The magnitude of our estimates shows that profit sharing is an economically relevant phenomenon in the US. Our approach also permits us to control for the extent of unionization and the degree of monopoly power in the goods market, shedding light on the relationship between insider variables and the degree of profit-sharing.

The chapter has four other sections. The models presented in the next section provide a framework for the empirical section and, in particular, organize the discussion

[7]For more details, we direct the reader to Shea (1993a).

[8]See Appendix 3 for comparisons between our sample and the entire manufacturing sector.

on simultaneity and measurement error issues. Section 3.3 describes the empirical methodology to be used, including the choice of instruments and the specification of each variable used in the estimation. Section 3.4 reports results for different specifications of the basic equation relating real wages and profits-per-worker derived in section 3.2 and provides our basic estimate for the profit-sharing coefficient. In addition, we analyze how insider variables affect this elasticity, real wages and profits-per-worker. The last section concludes.

3.2 Wages and profits

Including profitability measures in a real wage equation yields inconsistent estimates when OLS is used. Let us write the basic equation to be estimated as:

$$W = \gamma \frac{\Pi}{N} + Z + \eta \tag{3.1}$$

where γ is the profit-sharing parameter; W is the real wage; $\frac{\Pi}{N}$ is profits-per-worker; Z is a measure of the alternative wage; and η represents relevant omitted variables.

The estimation of equation (3.1) is problematic for several reasons:

- First, wages enter directly in the formula of the profits-per-worker variable with a negative sign. Everything else constant, there is a downward bias in estimates of γ. Profits-per-worker can be written as:

  $$\frac{\Pi}{N} = A\frac{f(N)}{N} - W \tag{3.2}$$

  where $Af(N)$ is value added; and A is the revenue-shifting parameter.[9]

  The following regression shows the OLS results for a panel of 450 4-digit US manufacturing industries. Year dummies are included to capture the effects of the alternative wage and any other year effects.

[9] In general, the parameter A will be a function of the technology and the demand for the final good. For a simple example, assume that labor is the only input, the production function is Cobb-Douglas, $X = A'N^{\alpha}$, X = output, A' = technological shocks, and that the product demand curve is, $X = A''P^{-k}$, A'' = demand-shifter, k = elasticity of demand. In this case, $A = A' * A''^{\frac{1}{k}}$.

$$(OLS)\quad W = \underset{(.002)}{.040}\ \frac{\Pi}{N} + Yeardummies \quad R^2 = 0.26$$

The problem of the downward biased γ can be solved if we estimate equation (3.2) using the real value added-per-worker as an instrumental variable. Assuming that the only source of simultaneity between wages and profits comes from the inclusion of wages in the profit-per-worker formula, this I.V. strategy would yield consistent estimates of γ.[10]

$$(IV)\quad W = \underset{(.002)}{.082}\ \frac{\Pi}{N} + Yeardummies$$

The I.V. estimate of the profit-sharing parameter is larger than the OLS estimate, as expected. Unfortunately, there are other possible sources of simultaneity between wages and profit-per-worker. In these cases, real value added-per-worker is not a good instrumental variable and we need to look for an alternative instrument.

- Most of the papers in this literature measure profits as the difference between sectoral (or firm) value added and the wage bill. The failure to take into account the cost of capital generates measurement error problems in real value added-per-worker. Several authors (Blanchflower *et al* (1993), for instance) take out depreciation allowances and the rental cost of capital, but the implicit hypotheses built in the calculation of these variables are sources of measurement errors in and of themselves. In this case, η in (3.1) represents measurement error and OLS estimates of γ will be inconsistent.

- Even if both of the above problems were not present, wages and profits-per-worker are endogenously determined if firms change employment to adjust for

[10]The variables are in natural logarithms. The regressions are run in first-differences to correct for sectoral fixed effects. The standard error (in parentheses) of the estimated parameter is calculated assuming the residual term follows a MA(1). For more information about the data see subsection 3.3.2.

autonomous variations in wages. As we are going to illustrate in the next section, this is the case in most bargaining models.

- Finally, as pointed out by Abowd and Lemieux (1993), heterogeneity among sectors may cause inconsistent estimates of γ if γ_i, the profit-sharing parameter of sector i, is correlated with $\frac{\Pi_i}{N_i}$. Since several papers, including this one, are interested in the average profit-sharing parameter for the whole economy, we rewrite (3.1) as:

$$W_i = \gamma \frac{\Pi_i}{N_i} + Z + \eta_i \quad , \quad \eta_i = \eta_i' + (\gamma_i - \gamma) \frac{\Pi_i}{N_i} \tag{3.3}$$

  η_i' represents other stochastic terms not included in (3.1).

  In this case, if γ_i is correlated with profits-per-worker (sectors with higher profit-per-person share less profit with their workers, for instance), the residual term will be correlated with the regressor and the OLS estimator will be inconsistent.

Let us turn to some simple bargaining models. These models will provide some structure for the analysis of the results and highlight a way to identify the parameter γ in equation (3.1).

3.2.1 Efficient bargaining

The first model to be presented assumes that workers and firms bargain over wages and employment in order to maximize the joint surplus of their economic activity.[11] If both parties do not reach an agreement they receive fallback incomes. Workers maximize the surplus expected utility derived from their income (expected utility minus a threat point defined by the fallback wage). The firm maximizes its surplus

[11]This explains the name "efficient bargaining". There is a discussion on what is the most appropriate specification for the objectives of the bargaining process. Layard *et al* (1991), chapter 2, shows the arguments against the efficient bargaining setup and in favor of the "right-to-manage" model where firms and workers bargain over wages only (to be presented below). Blanchflower *et al* (1992), for instance, use the efficient specification because the "right-to-manage" would be based upon "an explained inefficiency".

profits. We assume that the fallback or "strike" profit is equal to zero. The source of workers' bargaining power comes from their ability to act as a group. The ability to act as a group generates bargaining power, which is represented by the parameter, μ.

The Nash bargaining process can be summarized by maximization of:

$$\Omega = \Phi^{\mu}\Pi^{1-\mu} \tag{3.4}$$

where Φ is the surplus expected utility of a representative worker and Π is the profit level of the firm. The surplus expected utility of a representative worker can be defined as:

$$\Phi = N(v(W) - v(Z)) \tag{3.5}$$

where W is the real wage; N is the employment level; Z is the alternative wage; and $v(x)$ measures the utility derived by an individual from income x.

Equation (3.5) assumes that the alternative wage received by a worker if fired is also the fallback wage in case of a disagreement. Additionally, we choose the units of N so that N can also be interpreted as the probability of employment. The expected alternative income, Z, is a function of "outsider" variables: the unemployment rate, unemployment benefits, and the economy-wide average wage rate.

Let us write profits as:

$$\Pi = Af(N) - WN$$

where A is a revenue-shifting parameter.

The first-order conditions we get from maximizing (3.4) with respect to W and N are:

$$\beta\frac{\Pi}{N} = \frac{v(W) - v(Z)}{v'(W)} \tag{3.6}$$

$$W = \beta\frac{\Pi}{N} + Af'(N) \tag{3.7}$$

Linearizing $v(Z)$ around W, throwing away higher order terms, and rewriting both (3.6) and (3.7), we get:

$$W = \beta \frac{\Pi}{N} + Z \tag{3.8}$$

$$Af'(N) = Z \tag{3.9}$$

$\beta = \frac{\mu}{1-\mu}$ is the relative bargaining power of workers.

In this model, firms hire workers until labor productivity is equal to the alternative wage a worker would receive if fired. Therefore, the hiring decision of firms does not depend on the contracted wage. This is the "strongly efficient" bargaining case. Variations in the utility function of workers may generate the case where firms hire workers on the labor demand curve or where they equate labor productivity and a weighted average of Z and W. For instance, if we write the worker's utility as,

$$N^{\mu_1}(W - Z)^{\mu_2}$$

the optimal contract curve is:

$$Af' = \left(1 - \frac{\mu_1}{\mu_2}\right) W + \frac{\mu_1}{\mu_2} Z$$

The wage equation is still (3.8), where β is the ratio between μ_2 and the exponent on profits-per-worker in the Nash bargaining function. If $\mu_1 = 0$, we have a situation where workers do not care about employment. Incumbent workers may not care about employment if layoffs follow a seniority rule and the positions of incumbent employees are protected by substantial labor turnover costs.[12]

In either case, the profit-sharing coefficient, β, is independent of changes in profits-per-worker within each sector and changes in the revenue-shifter parameter, A, affect wages only through variations in the profits-per-worker variable. Therefore, variations

[12]See Lindbeck and Snower (1990) for an example of such a model.

in market conditions, which are summarized by shifts in A are transmitted to wages only through variations in profits-per-worker. By identifying exogenous changes in A, we are able to provide consistent estimates of the profit-sharing parameter using these revenue shifts as instruments.

3.2.2 Right-to-manage models

Some authors argue that bargaining between firms and workers is not efficient. Layard *et al* (1991) present factual evidence that both parties do not bargain over employment after all. Even if workers care about employment they may bargain over wages with the firm and let it fix the employment level that maximizes profit. The Nash bargaining function to be maximized is:

$$\Omega = (N(W)(v(W) - v(Z)))^{\mu}\Pi^{1-\mu} \tag{3.10}$$

Differentiating (3.10) with respect to W, using the fact that firms maximize profit, and linearizing $v(Z)$ around W, we get:

$$W = \gamma\frac{\Pi}{N} + Z \tag{3.11}$$

$$Af'(N) = W \tag{3.12}$$

The innovation introduced by this model is that the profit-sharing parameter will not be equal to β, the relative bargaining power of workers, but will be a function of β, profits-per-worker and the elasticity of labor demand, $\gamma = \gamma(\beta, \frac{\Pi}{N}, \epsilon)$.

Now, $\frac{\Pi}{N}$ cannot be considered a sufficient statistic for the product market conditions. Changes in A may affect real wages through changes in the elasticity of labor demand. Assuming that ϵ is constant allows the identification of (3.11) with revenue shifters.

The parameter of interest in equation (3.11) depends on the profits-per-worker variable. This dependence exacerbates the simultaneity problems caused by heterogeneity in γ which were pointed out earlier. In order to solve this problem without assuming any specific function for γ, we linearly approximate γ with respect to profits-per-worker:

$$\gamma(\frac{\Pi_i}{N_i}) = \gamma_0 + \gamma_1(\frac{\Pi_i}{N_i} - \frac{\overline{\Pi}}{N}) \tag{3.13}$$

where $\frac{\overline{\Pi}}{N}$ is average profit-per-worker.

We assume that the residual of this approximation is insignificant. Notice that the coefficient γ_1 is interesting in and of itself. Looking at the time dimension, a negative γ_1 means that profit-sharing decreases in good times and increases in bad times. Considering the cross-sectional dimension, sectors that have consistently higher profitability than the sample average, share a smaller percentage of profits-per-worker. The opposite is true if $\gamma_1 > 0$. We give further interpretations for this coefficient in the results section. The equation to be estimated in this case is:

$$W_i = \gamma_0\frac{\Pi_i}{N_i} + \gamma_1\frac{\Pi_i}{N_i}(\frac{\Pi_i}{N_i} - \frac{\overline{\Pi}}{N}) + Z + \eta_i \tag{3.14}$$

η_i is a stochastic term representing excluded variables and other random shocks.[13] Equation (3.14) can be consistently estimated if the instrumental variable used to

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[13]Using the specification in this simplified model, we can write $\gamma(\cdot)$ as

$$\gamma = \frac{\beta}{1 - \beta\tilde{\epsilon}\frac{\overline{\Pi}}{N}}$$

$$\tilde{\epsilon} = \frac{\partial N}{\partial W}\frac{1}{N} < 0$$

$\tilde{\epsilon}$ is the semi-elasticity of labor demand. We can identify (3.14) under the hypothesis that this semi-elasticity is constant. The equation is also identified if the elasticity of labor demand is constant, $\epsilon = \tilde{\epsilon}W = c$. In this case, we can specify an approximate linear specification for the relationship between real wages and profits-per-worker, if we first linearize γ with respect to wages, rewrite equation (3.11), and then linearize both the coefficients of $\frac{\Pi_i}{N_i}$ and Z. The final equation in this case would be:

$$W = \gamma_0\frac{\Pi_i}{N_i} + \xi_0 Z_i + \gamma_1\frac{\Pi_i}{N_i}(\frac{\Pi_i}{N_i} - \frac{\overline{\Pi}}{N}) + \xi_1 Z_i(\frac{\Pi_i}{N_i} - \frac{\overline{\Pi}}{N}) + \eta_i'$$

η_i' is a stochastic term representing excluded variables and other random shocks.

The interactive term between measures of the alternative wage and profits-per-worker proved to be insignificant in our regressions and it was excluded from the specifications we present in the results section.

identify revenue shifts is not correlated to the terms included in η_i.[14]

To summarize the last two subsections: revenue-shifters identify the profit-sharing parameter in common bargaining models. If we assume the right-to-manage model is the best description of the way firms and workers bargain over key labor market variables, additional assumptions on the elasticity of demand for labor are required in order to guarantee identification. If we assume bargaining is efficient, no such assumptions are necessary.

3.3 Empirical methodology and data description

3.3.1 Demand-shifters

The last section made the case for the use of revenue-shifters as good instruments for estimation of linear profit-sharing relationships. Either neutral technology shocks or exogenous variations in the demand for goods may be used as revenue shifters. We choose exogenous changes in demand as our revenue shifters because we can build this variable with a high degree of certainty that it is a good proxy for exogenous movements in A.

We perform a panel data analysis for the 4-digit sectors of the American manufacturing sector. One way of getting good demand shifters for this database is to use the input-output approach described in Shea (1993). Shea uses information from the input-output tables for two-, three-, and four-digit industries to choose variables that should be correlated with demand shifts of a particular 4-digit sector. Output of sector j is a good demand-shifter for sector i if sector j demands a large share of sector i's output, but sector i, and other sectors closely related to it, comprise a small share of the production costs to sector j. The first condition is to insure that output of sector j is relevant for identifying demand shifts. The second condition is to minimize the possible sensitivity of the output of sector j to price variations in

[14]We use the square of the revenue-shifters as an extra instrument.

sector i. Let us call the demand share of sector j, DS, and the cost share of sector i, CS.

Shea (1993a) shows that the asymptotic bias in the IV estimates of the supply elasticity obtained when using the input-output approach to select instruments is decreasing in the ratio, DS/CS. For a given ratio, increases in DS should increase the correlation between final and intermediate output. Using Monte-Carlo simulations, Shea shows that this increased correlation improves the small sample behavior of his estimates over some range. Therefore, variables with high DS/CS ratios are good demand-shifters, in the sense that they identify a supply elasticity with small asymptotic bias. Since we need good demand-shifters, the same results apply to our approach.[15]

This general rule is not enough to select potential instruments for sector i. It is important to impose rules on the process of instrument selection that minimize the influence of common supply shocks between both the sector we use as an instrument and the sector for which we need an instrument. For instance, sectors with the same two-digit SIC code as industry i are not eligible instruments for industry i. This prohibition reflects the assumption that supply shocks are highly correlated within a two-digit industry. For the same reason, industries belonging to different SIC groups that are subject to similar supply shocks were not used as instruments for one another.[16] In addition, the cost share data used in the instrument selection is the cost share of the two-digit sector containing industry i. For more details, see Shea (1991).

In summary, instruments chosen by this approach are good proxies for exogenous variation in A, the revenue-shifter. In other words, it is not plausible that variations in the price of sector i have a significant impact on the output of sector j because the share of sector i in sector j's cost is small. This methodology tends to generate instruments at a higher level of aggregation than the sector for which we are instru-

[15]The threshold values we used are $DS/CS > 3$ and $DS > 0.15$, the same used by Shea.

[16]This is the case for apparel and textile industries (SIC 23 and 22), primary and fabricated metals industries (SIC 33 and 34), machinery and eletrical machinery industries (SIC 35 and 36).

menting. Furthermore, many of the variables we use are ideal demand shifters when significantly related to sectoral output because they are obviously exogenous. Government defense spending is a good example of this. Changes in defense spending are more related to political and social movements than to specific 4-digit industry supply shocks.

The list of potential instruments for 150 4-digit industries that follow these rules can be found in Shea (1992). The problem with this list is that it does not guarantee that the relationship between the instrumental variable candidate and the output of sector i is a result of their input-output link. If the candidate follows business cycle variations closely, it may be a poor instrument. In this case, it is plausible to assume that the instrument does not represent exogenous shocks to revenue in sector i, because the cost variables in this sector may be significantly correlated to the business cycle themselves.

In order to solve this problem we pretested the potential instruments for relevance once business cycle variations were purged from the data. First, we regressed the potential instruments on business cycle measures and got the residuals from this equation.[17] Then we regressed output growth on the residual instrument growth to check for instrument relevance. We discarded instruments which had low $T * R^2$ statistics or were negatively correlated to the regressor.[18] The sectors chosen after this checking process are reported in Appendix 2.

Some sectors have only one good instrument, while others have more than one. In order to select one vector of instruments among all the available possibilities, we maximize the criterion which is used to guarantee instrument exogeneity. Hence, we choose the instrument which has the highest ratio of DS to CS. Using other criteria to generate the demand-shift vector generates similar results to those reported in the next section.

[17]Different measures were used. The final regressions use the total manufacturing price and production as business cycle indicators. The results are insensitive to the choice of other indicators.

[18]Although only a few instruments produce a negative correlation to output, we discarded them since systematic demand shocks should be related to variations in output in the same direction.

3.3.2 Data

Most of the data in this work comes from the Productivity Database compiled by Wayne B. Gray. For more details see Gray (1992). The basic original source is the Annual Survey of Manufactures. The wage is computed as the ratio of payroll to employment divided by the Consumer Price Index. The data on payroll and employment include production as well as non-production workers. Profits are computed as Value of Industry Shipments + Inventory change - Payroll - Costs of Materials.[19] Profits were then divided by employment. We proxied for the alternative annual average wage for each sector by including the average annual manufacturing wage (deflated by the CPI) and the unemployment rate for the whole economy in the estimated equation. Though data on production worker hours are available, we use the total number of workers as the employment variable because we want a sample which is representative of the whole labor force.[20]

For those industries whose instruments were other 4-digit industries, we used output created from the Gray database.[21] For those sectors whose instruments were two-digit industries, output was taken from Citibase. The sources of the additional instruments are available from us upon request.

3.4 Results

We discuss the basic results first, then turn to how these results change when we adopt alternative specifications, control for the degree of firms' monopoly power in the goods market, and control for the extent of unionization. The equation we estimate is:

[19] The last term is deflated by the Price of Materials Deflator while the other terms are deflated using the Value of Shipments Deflator.

[20] Using wages per production worker-hour and profits per production worker-hour yields similar results to our estimates. Using average work hours of production workers as a proxy for average work hours of the total workforce also does not change the results. See the next section for further details.

[21]

$$Y = \frac{ValueofShipments_t + Inventories_t - Inventories_{t-1}}{ValueofShipmentsDeflator_t} \tag{3.15}$$

$$W_{it} = \alpha_i + \gamma_0 \frac{\Pi_{it}}{N_{it}} + \gamma_1 \frac{\Pi_{it}}{N_{it}} (\frac{\Pi_{it}}{N_{it}} - \frac{\overline{\Pi}}{N}) + Z_t + \eta_{it} \tag{3.16}$$

α_i represents industry specific effects; η_{it} is a stochastic term representing excluded variables and other random shocks.

We assume that the alternative wage of a worker is the same for everyone, $Z_{it} = Z_t$. All variables enter as natural logarithms. We take first-differences to wash out fixed industry effects. The final specification is:

$$\Delta W_{it} = \gamma_0 \Delta \frac{\Pi_{it}}{N_{it}} + \gamma_1 \Delta (\frac{\Pi_{it}}{N_{it}} (\frac{\Pi_{it}}{N_{it}} - \frac{\overline{\Pi}}{N})) + \Delta Z_t + \Delta \eta_{it} \tag{3.17}$$

Under the assumption that η_{it} is white noise, we calculated the standard errors of our estimated parameters assuming that $\Delta\eta_{it}$ follows an MA(1) process. Table 3.1 shows the first stage regressions for real wage and profits-per-worker. It should be noted that it is not clear *a priori* what the relationship is between changes in demand and changes in profits-per-worker and wages. The effect of increases in output on profits-per-worker will depend on labor productivity, for instance. The results show that increases in demand increase profits-per-worker and wages. All the other exogenous variables are relevant as well. We also include a specification with time dummies to capture time effects. This specification is superior to the one that includes just the alternative wage, unemployment and a trend, because it takes care of these variables in addition to other relevant omitted variables without cross-sectional variation.

Table 3.2 presents the OLS and the IV results. The OLS estimates of the profit-sharing coefficient vary from .045 to .056, which are of the same order of magnitude as previous results. The specifications including the unemployment rate and the average industrial wage produce the expected signs, although the coefficient for unemployment is statistically insignificant. The coefficient of average industrial wages is close to one as expected. The quadratic term is not significant in the OLS estimates.

The IV results show a different picture. The profit-sharing coefficient in the preferred specifications of columns 7 and 8 is six times larger than the OLS estimates. Estimates in column 5 show the importance of including time dummies and the quadratic term in (3.17). This is the only specification that generates a positive sign for the coefficient on unemployment, a small value for the coefficient of the average industrial wage and a .55 profit-sharing parameter. The preferred specification is in column 8 where time dummies and the quadratic term are included. We estimate a profit-sharing parameter for the American manufacturing sector equal to .327.

We find a consistently negative coefficient for the quadratic term. This result shows that firms share a smaller (larger) proportion of their profit when profits-per-worker increase (decrease). This fact is consistent with a simple right-to-manage model where the profit-sharing parameter is inversely related to firms' profitability. Profit-sharing diminishes in good times and increases in bad times. Firms that are less profitable than average share more than more profitable firms. We give further evidence on this point below.

One could argue that the fact that we use variables that are not corrected by the number of hours each employee works may be biasing our IV estimates upward. In this scenario, the detected wage variations when the conditions in the product market change could be merely capturing the fact that average hours of work are positively related to demand shocks. Table 3.3 gives the results using two different definitions for the hourly wage and the profit-per-hour variables. The first two columns use the data for production workers. The last two columns use the average hours of production workers as a proxy for the average hours of all workers in a sector. Both OLS estimates are very similar to the results listed in the fourth column of Table 3.2. The IV results show that the point estimate for the profit-sharing parameter using production worker data is larger than the profit-sharing parameter when data for the whole labor force are used, although this difference is not statistically significant. The results for the total labor force in column four are equivalent to the results in Table 3.2.

Blanchflower *et al* (1993) test two alternative hypotheses for the positive coefficient on profits-per-worker. First, if the production function is Cobb-Douglas, we may be capturing an inverted labor demand curve. Wages will be positively related to profits-per-worker, even if workers and firms do not bargain over wages, because they are negatively correlated to employment and variations in employment cause smaller variations in profits in the same direction. So, if employment increases because wages decrease (workers' preference changes, for instance), profits are going to increase less than proportionately and profits-per-worker are going to be positively related to wages. The methodology we follow here dispenses with this hypothesis automatically because in the Cobb-Douglas case $\frac{\Pi}{N}$ is independent of shifts in demand (see McDonald and Solow (1981)). Therefore, we should not be able to identify equation (3.17) using demand-shifters as instruments - which is clearly not the case.

Second, the competitive model with labor mobility costs may also generate a positive relationship between profits-per-worker and wages in the short-run.[22] We introduce lags of $\frac{\Pi}{N}$ in our regressions in order to pick up this dynamic effect. Table 3.4 shows that the inclusion of these lags does not alter our results. The sum of their coefficients is essentially the same as if the lags were omitted. Additional specifications where lags of the interactive term and higher order lags were included generate the same result. Because the competitive model with labor mobility costs predicts a long-run elasticity of zero, we can reject it in favor of a bargaining model.

The profit-sharing parameter may vary across sectors for several reasons. The next set of results focuses on two different sources of variability in γ_0. First, some sectors produce more economic rents than others and there is no reason to assume that they share the same proportion of their profits. In other words, we are saying that the profit-sharing parameter, evaluated at average profits-per-worker, γ_0, can be different for groups of firms with different $\overline{\frac{\Pi}{N}}$.

One way of testing this effect is to break our sample using an exogenous variable which represents the ability of a sector to produce rents. We split our sample using a 4-firm concentration index for each sector. This index is a proxy for firms' market power and their ability to generate economic rents. Table 3.5 breaks the sample in two: sectors that have market power below the median level and sectors that have market power above the median level. The IV results show that profit-sharing is inversely

[22]This result is driven by the fact that in the short-run the labor supply curve would not be flat as in the traditional competitive model, but positively sloped.

related to market power, although the difference is not statistically significant due to high standard errors in the low market power sample. In other words, the higher the degree of monopoly power in a sector, the higher the profits-per-worker and the real wage paid, but the lower the proportion of profits that are shared.[23] This result is not very sensitive to how we split the sample.

Note that this effect is similar to the one suggested by the negative sign of the quadratic term coefficient. The difference in monopoly power across sectors cause differences in profitability which contributes to wage variation across industries, but the effect is dampened by the behavior of the profit-sharing parameter. Thus, the relationship between the profit-sharing parameter and market power diminishes the cross-sectional variability of wages. This result is robust to different breakpoints.

Another source of heterogeneity in γ is the variability of workers' bargaining power between sectors. We use the extent of unionization variable available in the NBER trade database, and described in Abowd (1990), to break our sample in two groups: sectors that have a high level of union penetration and sectors that have a low level of union penetration. Table 3.6 shows the OLS and IV results for both subsamples. Sectors where workers have little bargaining power (proxied by the extent-of-unionization variable) yield a higher profit-sharing parameter than sectors where workers have strong bargaining power, a puzzling result.

[23]The matrix of correlations of wage, profits-per-worker, the market concentration index and the extent of unionization is:

	W	$\frac{\Pi}{N}_t$	*Conc.*	*Union.*
W	1.000			
$\frac{\Pi}{N}_t$	.410	1.000		
Conc.	.468	.254	1.000	
Union.	.517	.113	.211	1.000

Regressions of wage and profits-per-worker on market concentration and extent of unionization captures the effect of one of these variables controlling for the other. Standard errors are in parentheses.

$$W = \underset{(.006)}{.10} * conc + \underset{(.014)}{.35} * union$$

$$\frac{\Pi}{N}_t = \underset{(.017)}{.12} * conc + \underset{(.042)}{.27} * union$$

Though this difference is statistically significant, different breaks in the sample generate different results. Table 3.7 splits the sample in three: low, medium and high unionized sectors. The results point to a u-shaped relationship between the extent of unionization and the profit-sharing parameter, although the differences between the coefficients are not statistically significant. Therefore, the empirical evidence is dubious with respect to the effect of unionization on the profit-sharing parameter. It seems that the previous results were driven by the behavior of sectors around the median value for the extent of unionization. However, since bargaining power may come from a variety of sources in our sample and not just from the extent of unionization, the results are less surprising. Further research using different proxy variables for workers' bargaining power is necessary in order to clarify this point.

3.5 Conclusions

Our work sheds new light on tests of labor market competitiveness. Previous authors claim that the very small elasticities of wage with respect to profits-per-worker they find are relevant nonetheless because profits-per-worker are so variable across industries that even a small elasticity generates an impact on wages. We estimate an elasticity which is six times as large as the previous results and our own OLS estimates (.33 as compared to .05). Changes in profits-per-worker have a relevant impact on wages regardless of the variation in profits-per-worker. Our methodology also provides evidence against alternative explanations for the positive correlation between profits-per-worker and wages such as a neoclassical model with labor mobility costs and a simple profit-maximization model with Cobb-Douglas technology.

Additionally, we study the sensitivity of the profit-sharing parameter to variations in its determinants. Changes in profits-per-worker have a dampening effect on profit-sharing. This effect is consistent with a simple right-to-manage model where the profit-sharing parameter varies inversely with profits-per-worker. More evidence on this point was obtained by splitting the sample using measures of industry market power in the goods market. Sectors that have more monopoly power tend to have more rents-per-employee and pay higher wages, but they share a smaller proportion of profits.

When we used the extent of worker unionization in a sector as a proxy for worker bargaining power we got puzzling results. The relationship between this variable and the profit-sharing parameter is not robust to different sample splits. This fact seems to be driven by the outlier behavior of sectors around median values of unionization. Our final evidence on this question establishes a weak u-shaped relationship between the extent of unionization and rent-sharing behavior. Further research is needed to understand the effect of workers' bargaining power - including bargaining power due to forces other than unions - on profit-sharing.

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3.7 Appendix 1: Tables of results

Table 3.1: First-stage regressions

	Wage	Wage	Profit per Worker	Profit per Worker
Demand Instrument	.018 (.001)	.016 (.007)	.033 (.007)	.044 (.007)
Average Wage	1.379 (.055)		1.717 (.244)	
Unemployment	-.041 (.007)		-.211 (.032)	
Trend	.001 (.000)		.002 (.000)	
Year dummies	NO	YES	NO	YES
$\bar{R}^2$	.28	.23	.05	.10

Sample size: 1703. Standard errors in parentheses. All regressions run in differences of logs.

Table 3.2: The effect of profits on wages

	OLS	OLS	OLS	OLS	IV[a]	IV[b]	IV[c]	IV[d]
$\frac{\Pi}{Nt}$	.048	.054	.056	.045	.551	.354	.368	.327
	(.006)	(.006)	(.011)	(.011)	(.120)	(.063)	(.040)	(.041)
$\frac{\Pi}{Nt}\left(\frac{\Pi}{Nt} - \pi\right)$			-.004	.005			-.125	-.075
			(.005)	(.005)			(.017)	(.022)
Average	1.179		1.183		.434		1.1375	
Wage	(.055)		(.056)		(.222)		(.080)	
Unemployment	-.007		-.008		.075		-.003	
	(.007)		(.007)		(.026)		(.010)	
Trend	.001		.001		-.000		.001	
	(.000)		(.000)		(.000)		(.000)	
Year dummies	NO	YES	NO	YES	NO	YES	NO	YES
$\bar{R}^2$	.26	.28	.26	.28				

Sample size: 1703. Standard errors in parentheses. All regressions run in differences of logs.
[a] List of instruments: Demand shift vector, average wage, unemployment, trend.
[b] List of instruments: Demand shift vector, year dummies.
[c] List of instruments: Demand shift vector, Demand shift squared, average wage, unemployment, trend.
[d] List of instruments: Demand shift vector, Demand shift squared, year dummies.

Table 3.3: The effect of profits-per-hour on hourly wages

	Prod. workers	Prod. workers	Total workers	Total workers
	OLS	IV	OLS	IV
$\frac{\Pi}{Nt}$	.048	.752	.055	.303
	(.006)	(.396)	(.006)	(.144)
$\frac{\Pi}{Nt}\left(\frac{\Pi}{Nt} - \pi\right)$	.010	-.201	.013	-.050
	(.002)	(.101)	(.002)	(.045)
Year dummies	YES	YES	YES	YES
$\bar{R}^2$	.23		.28	

Sample size: 1703. Standard errors in parentheses. All regressions run in differences of logs.
List of instruments: Demand shift vector, Demand shift squared, year dummies.

Table 3.4: Estimations including lagged profits-per-worker

	OLS	IV[a]
$\frac{\Pi}{N}_t$	.053	.327
	(.011)	(.041)
$\frac{\Pi}{N}_t \left(\frac{\Pi}{N}_t - \pi\right)$	.002	-.076
	(.005)	(.025)
$\frac{\Pi}{N}_{t-1}$	.009	.022
	(.006)	(.046)
$\frac{\Pi}{N}_{t-2}$	.000	-.022
	(.006)	(.049)
Year dummies	YES	YES
$\bar{R}^2$	.29	

Sample size: 1642. Standard errors in parentheses. All regressions run in differences of logs.
List of instruments: Contemporaneous and two lags of the demand shift vector, demand shift squared, year dummies.

Table 3.5: Product market concentration

	OLS	OLS	IV	IV
	Low Conc	High Conc	Low Conc	High Conc
$\frac{\Pi}{N}_t$	.100	.025	.789	.300
	(.025)	(.011)	(.260)	(.056)
$\frac{\Pi}{N}_t \left(\frac{\Pi}{N}_t - \pi\right)$	-.008	.002	-.348	-.052
	(.011)	(.006)	(.150)	(.024)
Year dummies	YES	YES	YES	YES
$\bar{R}^2$	.31	.31		
Obs.	821	868	821	868

Standard errors in parentheses. All regressions run in differences of logs.
List of instruments: Demand shift vector, demand shift squared, year dummies. The product market concentration index is the 4-firm concentration index found in the NBER database. The sample was broken at the medium value for market concentration, 41.0%. The results are robust to different breaks.

Table 3.6: Extent of unionization

	OLS	OLS	IV	IV
	Low Union	High Union	Low Union	High Union
$\frac{\Pi}{N\,t}$	.066	.018	.620	.270
	(.015)	(.174)	(.083)	(.054)
$\frac{\Pi}{N\,t}\left(\frac{\Pi}{N\,t} - \pi\right)$	-.009	.023	-.140	-.069
	(.007)	(.008)	(.420)	(.039)
Year dummies	YES	YES	YES	YES
$\bar{R}^2$	.28	.28		
Obs.	827	893	827	893

Standard errors in parentheses. All regressions run in differences of logs.
List of instruments: Demand shift vector, demand shift squared, year dummies. The extent of unionization variable is the one constructed by Abowd and Farber (1990). The medium value for the extent of unionization for production workers is 48.5%. This result is not robust to different break points. See Table 3.7.

Table 3.7: Extent of unionization (cont.)

	IV	IV	IV
	Low Union.	Medium Union.	High Union.
$\frac{\Pi}{N\,t}$	.394	.260	.696
	(.149)	(.051)	(.228)
$\frac{\Pi}{N\,t}\left(\frac{\Pi}{N\,t} - \pi\right)$	-.072	-.061	-.252
	(.034)	(.035)	(.131)
Year dummies	YES	YES	YES
Obs.	467	803	450

Standard errors in parentheses. All regressions run in differences of logs.
List of instruments: Demand shift vector, demand shift squared, year dummies. The extent of unionization variable is the one constructed by Abowd and Farber (1990). We split the sample in three choosing the 25th. and 75th. percentile cutoff points, 34.3% and 56.9%, respectively.

3.8 Appendix 2: Demand-shifting instruments

SIC	Industry	Instrument
2097	Manufactured ice	Fishing*
2291	Felt Goods	Nonelectrical Equipment*
2293	Padding & Upholstery Filling	Transportation Equipment*
2396	Automotive and Apparel Trimmings	Vehicles*
2421	Sawmills and Planing Mills, general	Residential Const.*
2426	Hardwood Dimension and Floor Mills	Construction*
2431	Millwork	Construction*
		Residential Const.
2434	Wood Kitchen Cabinets	Construction*
		Residential Const.
2435	Veneer and Plywood	Construction*
		Residential Const.
2439	Structural Wood Members, n.e.c.	Construction*
		Residential Const.
		Nonresidential Const.
2452	Prefabricated Wood Buildings	Construction*
		Residential Const.
		Nonresidential Const.
2492	Particleboard	Construction*
2517	TV & Radio Furniture	Electrical Equipment*
		Radios & TVs
2649	Miscellaneous Conv. Paper	Construction*
2753	Engraving and Plate Printing	Finance, Insurance, Real estate*
2874	Nitrogeneous and Phosphatic Fertilizers	Agriculture*
2891	Adhesives and Sealants	Construction
		Residential Const.*
2892	Explosives	Coal Mining*
2893	Printing ink	Publishing*
2951	Paving Mixtures and Blocks	Construction*
		Nonresidential Construction
2952	Asphalt Felts and Coatings	Construction
		Residential Const.
		One-unit Construction*
3251	Brick & Structural Clay Tile	Construction*
		Residential Const.
		One-unit Construction
		Nonresidential Const.
3253	Ceramic Wall and Floor Tile	Construction*
		Residential Const.
		Nonresidential Const.
3259	Structural Clay Products, n.e.c.	Construction*
		Residential Const.
		One-unit Construction
		Nonresidential Const.
3261	Vitreous Plumbing Fixtures	Construction*
		Residential Const.
		One-unit Construction
		Nonresidential Const.
3264	Porcelain Electric Supplies	Nonresidential Const.

		Electrical Equip.*
3271	Concrete Block and Brick	Construction*
		Residential Const.
		One-unit Construction
		Nonresidential Const.
3272	Concrete Products, n.e.c.	Construction*
		Nonresidential Const.
3273	Ready-mixed Concrete	Construction*
		Residential Const.
		One-unit construction
		Nonresidential Const.
3274	Lime	Primary Metals
		Steel Mills*
		Basic Steel and Mills
3275	Gypsum	Construction*
		Residential Const.
		One-unit Construction
3291	Abrasive Products	Nonelectrical equipment*
3293	Gaskets, Packing and Sealing Devices	Nonelectrical equipment*
		Transportation Equipment
3296	Mineral wood	Construction*
		Residential Const.
		One-unit Construction
3299	Nonmetallic Mineral Products, n.e.c.	Primary Metals*
3357	Nonferrous Wire	Construction*
3431	Metal Sanitary Ware	Construction
		Residential Const.*
		One-unit Const.
3432	Plumbing Fixture Fittings & Trim	Construction
		Residential Const.*
		One-unit Const.
3441	Fabricated Structural Metals	Nonresidential Const.*
3442	Metal Doors, Sash and Trim	Construction
		Residential Const.*
		One-unit Const.
3449	Miscellaneous Metal work	Nonresidential Const.*
3463	Nonferrous Forgings	Aerospace*
3465	Automotive Stampings	Transportation Equipment*
		Autos
3482	Small Arms Ammunition	Federal Defense Spending*
3483	Other Ammunition	Federal Defense Spending*
3489	Other Ordnance	Federal Defense Spending*
3493	Steel Springs, except wire	Transportation Equipment*
		Autos
3534	Elevators & Moving Stairways	Nonresidential Const.*
3547	Rolling Mill Machinery	Primary Metals*
		Iron & Steel
3565	Industrial Patterns	Primary Metals*
		Iron & Steel
		Basic Steel and Mills
3567	Industrial Furnaces	Primary Metals*
3624	Carbon and Graphite	Primary Metals*
3662	Radio & TV Communication Equipment	Federal Defense Spending*
3672	Electron Tubes	Federal Defense Spending*

3676	Other Electronics	Federal Defense Spending*
3694	Engine Electrical Equipment	Autos*
3721	Aircraft	Federal Defense Spending*
3724	Aircraft & Missile Engines & Parts	Federal Defense Spending*
3761	Guided Missiles and Space Vehicles	Federal Defense Spending*
3764	Aircraft & Missile Engines & Parts	Federal Defense Spending*
3825	Mechanical Measuring Devices	Electrical equipment*
3843	Dental Equipment and Supplies	Federal health spending*
3996	Hard Surface and Floor Coverings	Construction*
		Residential Const.
		One-unit Const.

* Series actually included in the demand-shifter variable.

3.9 Appendix 3: Sample comparisons

In the text, we state that our sample is representative of the entire US manufacturing sector. The table below shows the distribution of the key variables for both the entire sample and the sample used in this work. Wages and profits are in thousands of 1982 dollars per person. Profits-per-worker in the entire sample have a slightly larger right tail but other than that wages and profits are very similar. Union penetration and the 4-firm concentration numbers are also very similar across the two samples. The results in the text are not being driven by sample selection and they are representative of manufacturing in general.

	Wages		Profits		Union		Concentration	
	Full Sample	Our Sample	Full Sample	Our Sample	Full Sample	Our Sample	Full Sample	Our Sample
10%	12.22	14.87	9.76	10.71	28.8	31.9	14.6	12.0
30%	16.09	17.58	14.74	15.67	35.0	37.8	24.7	27.9
50%	18.83	19.94	19.93	20.19	42.3	48.5	35.3	41.0
70%	21.16	21.78	27.11	25.69	51.9	51.5	47.7	54.7
90%	24.67	25.66	51.40	38.40	61.1	61.0	68.2	74.8