"THE ROLE OF PROFITS IN WAGE DETERMINATION: EVIDENCE FROM US MANUFACTURING"

MARCELLO ESTEVÃO

MIT

LOCAL: Fundação Getulio Vargas
       Praia de Botafogo, 190 - 10º andar
       Auditório

DATA: 27/07/95 (5ª feira)

HORÁRIO: 16:00h
The Role of Profits in Wage Determination:

Evidence from US Manufacturing

Marcello Estevão

Stacey Tevlin*

Department of Economics - MIT

November, 1994

*We benefited from insightful discussions with Joshua Angrist, Olivier Blanchard, Ricardo Caballero, Steve Pischke and Robert Solow. Beth Anne Wilson provided valuable suggestions. We would also like to thank the participants of the Money and Labor Lunch Seminars at MIT for their comments. We are responsible for all remaining errors. Financial support from CNPq-Brazil and the Federal Reserve Bank of Boston is gratefully acknowledged.
The Role of Profits in Wage Determination
Evidence from US Manufacturing

Abstract

We estimate the effect of firms' profitability on wage determination for the American economy. Two standard bargaining models are used to illustrate the problems caused by the endogeneity of profits-per-worker in a real wage equation. The profit-sharing parameter can be identified with instruments which shift demand. Using information from the input-output table, we create demand-shift variables for 63 4-digit sectors of the US manufacturing sector. 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 unionization and product market concentration reinforces our results.

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 paper 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 (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.\textsuperscript{1}

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 real wage paid to a worker.\textsuperscript{2} 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.\textsuperscript{3}

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. Our paper follows a different approach. We regress real wages on profits-per-worker and the alternative wage.\textsuperscript{4} Previous studies that follow this approach find that the profit-sharing coefficient is positive and significantly different from zero.\textsuperscript{5} 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

\textsuperscript{1}See Blanchflower \textit{et al} (1992).

\textsuperscript{2}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”.

\textsuperscript{3}Dickens and Katz (1987) and Layard \textit{et al} (1991) describe these results in detail. Blanchflower \textit{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.

\textsuperscript{4}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.

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 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 paper. The sample used is representative of the whole US manufacturing sector. 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 paper has four other sections. The models presented in the next section provide a framework for the empirical section and, in particular, organize the discussion on simultaneity and measurement error issues. Section 3 describes the empirical methodology to be used, including the choice of instruments and the specification of each variable used in the estimation. Section 4 reports results for different specifications of the basic equation relating real wages and profits-per-worker derived in section 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.

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:

---

\[ \text{wages} = \beta \text{profits} + \text{other variables} \]

---

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

See Appendix 2 for comparisons between our sample and the entire manufacturing sector.
\[ W = \gamma \frac{\Pi}{N} + Z + \eta \]  

(1)

where \( \gamma \) 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 \( \eta \) represents relevant omitted variables.

The estimation of equation (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 \( \gamma \). Profits-per-worker can be written as:

\[ \frac{\Pi}{N} = A \frac{f(N)}{N} - W \]  

(2)

where \( A f(N) \) is value added; and \( A \) is the revenue-shifting parameter.  

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.

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

The problem of the downward biased \( \gamma \) can be solved if we estimate equation (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

\[ A = A' * A'' \]

---

8In 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, \( X = A' N^a \), \( X \) = 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, \( A = A' * A'' \).
the profit-per-worker formula, this I.V. strategy would yield consistent estimates of $\gamma$.\footnote{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 3.2.}

\[(IV) \quad W = 0.082 \frac{\Pi}{N} + Yeardummies\]

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, $\eta$ in (1) represents measurement error and OLS estimates of $\gamma$ 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 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 $\gamma$ if $\gamma_i$, 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 (1) as:

$$W_i = \gamma \frac{\Pi_i}{N_i} + Z + \eta_i \quad \eta_i = \eta'_i + (\gamma_i - \gamma) \frac{\Pi_i}{N_i}$$

(3)

$\eta'_i$ represents other stochastic terms not included in (1).

In this case, if $\gamma_i$ 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 $\gamma$ in equation (1).

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.\textsuperscript{10} 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 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

\textsuperscript{10}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".
parameter, $\mu$.

The Nash bargaining process can be summarized by maximization of:

$$\Omega = \Phi^\mu \Pi^{1-\mu}$$  \hspace{1cm} (4)

where $\Phi$ is the surplus expected utility of a representative worker and $\Pi$ is the profit level of the firm. The surplus expected utility of a representative worker can be defined as:

$$\Phi = N(v(W) - v(Z))$$  \hspace{1cm} (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 (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 (4) with respect to $W$ and $N$ are:
\[
\beta \frac{\Pi}{N} = \frac{v(W) - v(Z)}{v'(W)}
\]  
(6)

\[
W = \beta \frac{\Pi}{N} + Af'(N)
\]  
(7)

Linearizing \(v(Z)\) around \(W\), throwing away higher order terms, and rewriting both (6) and (7), we get:

\[
W = \beta \frac{\Pi}{N} + Z
\]  
(8)

\[
Af'(N) = Z
\]  
(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 (8), where \( \beta \) is the ratio between \( \mu_2 \) 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.\(^{11}\)

In either case, the profit-sharing coefficient, \( \beta \), 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 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.

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:

\(^{11}\)See Lindbeck and Snower (1990) for an example of such a model.
\[
\Omega = (N(W)(v(W) - v(Z)))^{\mu \Pi^{1-\mu}}
\]  

(10)

Differentiating (10) with respect to \( W \), using the fact that firms maximize profit, and linearizing \( v(Z) \) around \( W \), we get:

\[
W = \gamma \frac{\Pi}{N} + Z
\]  

(11)

\[
Af'(N) = W
\]  

(12)

The innovation introduced by this model is that the profit-sharing parameter will not be equal to \( \beta \), the relative bargaining power of workers, but will be a function of \( \beta \), 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 \( \epsilon \) is constant allows the identification of (11) with revenue shifters.

The parameter of interest in equation (11) depends on the profits-per-worker variable. This dependence exacerbates the simultaneity problems caused by heterogeneity in \( \gamma \) which were pointed out earlier. In order to solve this problem without assuming any specific function for \( \gamma \), we linearly approximate \( \gamma \) with respect to profits-per-worker:

\[
\gamma \left( \frac{\Pi_i}{N_i} \right) = \gamma_0 + \gamma_1 \left( \frac{\Pi_i}{N_i} - \frac{\Pi}{N} \right)
\]  

(13)

where \( \frac{\Pi}{N} \) is average profit-per-worker.
We assume that the residual of this approximation is insignificant. Notice that the coefficient $\gamma_1$ is interesting in and of itself. Looking at the time dimension, a negative $\gamma_1$ 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:

$$W_i = \gamma_0 \frac{\Pi_i}{N_i} + \gamma_1 \frac{\Pi_i}{N_i} (\frac{\Pi_i}{N} - \frac{\Pi}{N}) + Z + \eta_i$$  \hspace{1cm} (14)

$\eta_i$ is a stochastic term representing excluded variables and other random shocks. Equation (14) can be consistently estimated if the instrumental variable used to identify revenue shifts is not correlated to the terms included in $\eta_i$.

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 de-

---

\[\beta = \frac{\beta}{1 - \beta \hat{e}}\]

$\hat{e}$ is the semi-elasticity of labor demand. We can identify (14) under the hypothesis that this semi-elasticity is constant. The equation is also identified if the elasticity of labor demand is constant, $\epsilon = \epsilon W = c$. In this case, we can specify an approximate linear specification for the relationship between real wages and profits-per-worker, if we first linearize $\gamma$ with respect to wages, rewrite equation (11), and then linearize both the coefficients of $\frac{\Pi_i}{N_i}$ and $Z$. The final equation in this case would be:

$$W = \gamma_0 \frac{\Pi_i}{N_i} + \epsilon_0 Z_i + \gamma_1 \frac{\Pi_i}{N_i} (\frac{\Pi_i}{N} - \frac{\Pi}{N}) + \epsilon_1 Z_i (\frac{\Pi_i}{N} - \frac{\Pi}{N}) + \eta_i$$

$\eta_i$ 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.

---

\[\eta_i\] We use the square of the revenue-shifters as an extra instrument.
scription 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 Empirical methodology and data description

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 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.\textsuperscript{14}

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.\textsuperscript{15} 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 instrumenting. Furthermore, many of the variables

\textsuperscript{14}The threshold values we used are $DS/CS > 3$ and $DS > 0.15$, the same used by Shea.
\textsuperscript{15}This is the case for apparel and textile industries (SIC 23 and 22), primary and fabricated metals industries (SIC 33 and 34), machinery and electrical machinery industries (SIC 35 and 36).
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.\(^{16}\) 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.\(^{17}\) The sectors chosen after this checking process are reported in Appendix 1.

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

---

\(^{16}\)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.

\(^{17}\)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.
similar results to those reported in the next section.

3.2 Data

Most of the data in this paper 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. 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.

For those industries whose instruments were other 4-digit industries, we used output created from the Gray database. 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.

18The last term is deflated by the Price of Materials Deflator while the other terms are deflated using the Value of Shipments Deflator.

19Using 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.

20

$$Y = \frac{Value of Shipments_t + Inventories_t - Inventories_{t-1}}{Value of Shipments Deflator_t}$$ (15)
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:

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

(16)

$\alpha_i$ represents industry specific effects; $\eta_{it}$ 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:

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

(17)

Under the assumption that $\eta_{it}$ is white noise, we calculated the standard errors of our estimated parameters assuming that $\Delta \eta_{it}$ follows an MA(1) process. Table 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 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 (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 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 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 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 (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 rela-
tionship between profits-per-worker and wages in the short-run.\textsuperscript{21} We introduce lags of $\frac{d}{d}$ in our regressions in order to pick up this dynamic effect. Table 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 $\gamma_0$. 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, $\gamma_0$, can be different for groups of firms with different $\frac{\gamma}{N}$.

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 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 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.\textsuperscript{22} This

\textsuperscript{21}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.

\textsuperscript{22}The matrix of correlations of wage, profits-per-worker, the market concentration index and the extent of...
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 $\gamma$ 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 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.

Though this difference is statistically significant, different breaks in the sample generate unionization is:

<table>
<thead>
<tr>
<th></th>
<th>$W$</th>
<th>$\Pi/N_t$</th>
<th>Conc.</th>
<th>Union.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W$</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Pi/N_t$</td>
<td>.410</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conc.</td>
<td>.468</td>
<td>.254</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Union.</td>
<td>.517</td>
<td>.113</td>
<td>.211</td>
<td>1.000</td>
</tr>
</tbody>
</table>

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.

\[
W = .10 \times \text{conc} + .35 \times \text{union} \\
\text{conc} = (0.006), \quad \text{union} = (0.014)
\]

\[
\Pi/N_t = .12 \times \text{conc} + .27 \times \text{union} \\
\text{conc} = (0.017), \quad \text{union} = (0.042)
\]
different results. Table 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.

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.
Table 1: First-stage Regressions

<table>
<thead>
<tr>
<th></th>
<th>Wage</th>
<th>Wage</th>
<th>Profit per Worker</th>
<th>Profit per Worker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand Instrument</td>
<td>.018</td>
<td>.016</td>
<td>.033</td>
<td>.044</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.007)</td>
<td>(.007)</td>
<td>(.007)</td>
</tr>
<tr>
<td>Average Wage</td>
<td>1.379</td>
<td></td>
<td>1.717</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.055)</td>
<td></td>
<td>(.244)</td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>-.041</td>
<td></td>
<td>-.211</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td></td>
<td>(.032)</td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>.001</td>
<td></td>
<td>.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.000)</td>
<td></td>
<td>(.000)</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>(R^2)</td>
<td>.28</td>
<td>.28</td>
<td>.05</td>
<td>.10</td>
</tr>
</tbody>
</table>

Sample size: 1703. Standard errors in parentheses. All regressions run in differences of logs.
Table 2: The Effect of Profits on Wages

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>OLS</th>
<th>OLS</th>
<th>OLS</th>
<th>IV(^a)</th>
<th>IV(^b)</th>
<th>IV(^c)</th>
<th>IV(^d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{\mu} N_t )</td>
<td>.048</td>
<td>.054</td>
<td>.056</td>
<td>.045</td>
<td>.551</td>
<td>.354</td>
<td>.368</td>
<td>.327</td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td>(.006)</td>
<td>(.011)</td>
<td>(.011)</td>
<td>(.120)</td>
<td>(.063)</td>
<td>(.040)</td>
<td>(.041)</td>
</tr>
<tr>
<td>( \bar{\mu} N_t (\bar{\mu} N_t - \pi) )</td>
<td>-.048</td>
<td>.005</td>
<td>-.125</td>
<td>-.075</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td>(.005)</td>
<td>(.005)</td>
<td>(.005)</td>
<td>(.120)</td>
<td>(.063)</td>
<td>(.040)</td>
<td>(.041)</td>
</tr>
<tr>
<td>Average Wage</td>
<td>1.179</td>
<td>1.183</td>
<td>.434</td>
<td>1.1375</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.055)</td>
<td>(.056)</td>
<td>(.222)</td>
<td>(.080)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>-.007</td>
<td>-.008</td>
<td>.075</td>
<td>-.003</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.007)</td>
<td>(.026)</td>
<td>(.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>.001</td>
<td>.001</td>
<td>-.000</td>
<td>.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.000)</td>
<td>(.000)</td>
<td>(.000)</td>
<td>(.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.26</td>
<td>.28</td>
<td>.26</td>
<td>.28</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Prod. workers</th>
<th>Prod. workers</th>
<th>Total workers</th>
<th>Total workers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>( \bar{\mu} N_t )</td>
<td>.048</td>
<td>.752</td>
<td>.055</td>
<td>.303</td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td>(.396)</td>
<td>(.006)</td>
<td>(.144)</td>
</tr>
<tr>
<td>( \bar{\mu} N_t (\bar{\mu} N_t - \pi) )</td>
<td>.010</td>
<td>-.201</td>
<td>.013</td>
<td>-.050</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.101)</td>
<td>(.002)</td>
<td>(.045)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.23</td>
<td>.28</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 4: Estimations including lagged profits-per-worker

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV*</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\Pi}{N_t}$</td>
<td>.053</td>
<td>.327</td>
</tr>
<tr>
<td></td>
<td>(.011)</td>
<td>(.041)</td>
</tr>
<tr>
<td>$\frac{\Pi}{N_t} \left( \frac{\Pi}{N_t} - \pi \right)$</td>
<td>.002</td>
<td>-.076</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td>(.025)</td>
</tr>
<tr>
<td>$\frac{\Pi}{N_t-1}$</td>
<td>.009</td>
<td>.022</td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td>(.046)</td>
</tr>
<tr>
<td>$\frac{\Pi}{N_t-2}$</td>
<td>.000</td>
<td>-.022</td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td>(.049)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.29</td>
<td></td>
</tr>
</tbody>
</table>

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 5: Product Market Concentration

<table>
<thead>
<tr>
<th></th>
<th>OLS Low Conc</th>
<th>OLS High Conc</th>
<th>IV Low Conc</th>
<th>IV High Conc</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\Pi}{N_t}$</td>
<td>.100 (.025)</td>
<td>.025 (.011)</td>
<td>.789 (.260)</td>
<td>.300 (.056)</td>
</tr>
<tr>
<td>$\frac{\Pi}{N_t} \left( \frac{\Pi}{N_t} - \pi \right)$</td>
<td>-.008 (.011)</td>
<td>.002 (.006)</td>
<td>-.348 (.150)</td>
<td>-.052 (.024)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.31</td>
<td>.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>821</td>
<td>868</td>
<td>821</td>
<td>868</td>
</tr>
</tbody>
</table>

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 6: Extent of unionization

<table>
<thead>
<tr>
<th></th>
<th>OLS Low Union</th>
<th>OLS High Union</th>
<th>IV Low Union</th>
<th>IV High Union</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{N_t}{N_t} )</td>
<td>.066 (.015)</td>
<td>.018 (.174)</td>
<td>.620 (.083)</td>
<td>.270 (.054)</td>
</tr>
<tr>
<td>( \frac{N_t}{N_t} (\frac{N_t}{N_t} - \pi) )</td>
<td>-.009 (.007)</td>
<td>.023 (.008)</td>
<td>-.140 (.420)</td>
<td>-.069 (.039)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.28</td>
<td>.28</td>
<td>.28</td>
<td>.28</td>
</tr>
<tr>
<td>Obs.</td>
<td>827</td>
<td>893</td>
<td>827</td>
<td>893</td>
</tr>
</tbody>
</table>

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 7.

Table 7: Extent of unionization

<table>
<thead>
<tr>
<th></th>
<th>IV Low Union</th>
<th>IV Medium Union</th>
<th>IV High Union</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{N_t}{N_t} )</td>
<td>.394 (.149)</td>
<td>.260 (.051)</td>
<td>.696 (.228)</td>
</tr>
<tr>
<td>( \frac{N_t}{N_t} (\frac{N_t}{N_t} - \pi) )</td>
<td>-.072 (.034)</td>
<td>-.061 (.035)</td>
<td>-.252 (.131)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Obs.</td>
<td>467</td>
<td>803</td>
<td>450</td>
</tr>
</tbody>
</table>

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.
## Appendix 1

### DEMAND-SHIFTING INSTRUMENTS

<table>
<thead>
<tr>
<th>SIC</th>
<th>Industry</th>
<th>Instrument</th>
</tr>
</thead>
<tbody>
<tr>
<td>2097</td>
<td>Manufactured ice</td>
<td>Fishing</td>
</tr>
<tr>
<td>2219</td>
<td>Felt Goods</td>
<td>Nonelectrical Equipment</td>
</tr>
<tr>
<td>2293</td>
<td>Padding &amp; Upholstery Filling</td>
<td>Transportation Equipment</td>
</tr>
<tr>
<td>2396</td>
<td>Automotive and Apparel Trimmings</td>
<td>Vehicles</td>
</tr>
<tr>
<td>2421</td>
<td>Sawmills and Planing Mills, general</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>2426</td>
<td>Hardwood Dimension and Floor Mills</td>
<td>Construction</td>
</tr>
<tr>
<td>2431</td>
<td>Millwork</td>
<td>Construction</td>
</tr>
<tr>
<td>2434</td>
<td>Wood Kitchen Cabinets</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>2435</td>
<td>Veneer and Plywood</td>
<td>Construction</td>
</tr>
<tr>
<td>2439</td>
<td>Structural Wood Members, n.e.c.</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>2452</td>
<td>Prefabricated Wood Buildings</td>
<td>Construction</td>
</tr>
<tr>
<td>2492</td>
<td>Particleboard</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>2517</td>
<td>TV &amp; Radio Furniture</td>
<td>Nonresidential Const.</td>
</tr>
<tr>
<td>2649</td>
<td>Miscellaneous Conv. Paper</td>
<td>Construction</td>
</tr>
<tr>
<td>2753</td>
<td>Engraving and Plate Printing</td>
<td>Electrical Equipment</td>
</tr>
<tr>
<td>2874</td>
<td>Nitrogenous and Phosphatic Fertilizers</td>
<td>Radio &amp; TVs</td>
</tr>
<tr>
<td>2891</td>
<td>Adhesives and Sealants</td>
<td>Construction</td>
</tr>
<tr>
<td>2892</td>
<td>Explosives</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>2893</td>
<td>Printing ink</td>
<td>Publishing</td>
</tr>
<tr>
<td>2951</td>
<td>Paving Mixtures and Blocks</td>
<td>Nonresidential Construction</td>
</tr>
<tr>
<td>2952</td>
<td>Asphalt Felts and Coatings</td>
<td>Construction</td>
</tr>
<tr>
<td>3251</td>
<td>Brick &amp; Structural Clay Tile</td>
<td>Residential Const.</td>
</tr>
<tr>
<td>3253</td>
<td>Ceramic Wall and Floor Tile</td>
<td>One-unit Construction</td>
</tr>
<tr>
<td>3259</td>
<td>Structural Clay Products, n.e.c.</td>
<td>Nonresidential Const.</td>
</tr>
<tr>
<td>3261</td>
<td>Vitreous Plumbing Fixtures</td>
<td>Construction</td>
</tr>
</tbody>
</table>
3264 Porcelain Electric Supplies
3271 Concrete Block and Brick
3272 Concrete Products, n.e.c.
3273 Ready-mixed Concrete
3274 Lime
3275 Gypsum
3291 Abrasive Products
3293 Gaskets, Packing and Sealing Devices
3296 Mineral wood
3299 Nonmetallic Mineral Products, n.e.c.
3357 Nonferrous Wire
3431 Metal Sanitary Ware
3432 Plumbing Fixture Fittings & Trim
3441 Fabricated Structural Metals
3442 Metal Doors, Sash and Trim
3449 Miscellaneous Metal work
3463 Nonferrous Forgings
3465 Automotive Stampings
3482 Small Arms Ammunition
3483 Other Ammunition
3489 Other Ordnance
3493 Steel Springs, except wire
3534 Elevators & Moving Stairways
3547 Rolling Mill Machinery
3565 Industrial Patterns

Residential Const.
One-unit Construction
Nonresidential Const.
Nonresidential Const.
Electrical Equip.
Construction
Residential Const.
One-unit Construction
Nonresidential Const.
Construction
Nonresidential Const.
Construction
Residential Const.
One-unit construction
Nonresidential Const.
Primary Metals
Steel Mills
Basic Steel and Mills
Construction
Residential Const.
One-unit Construction
Nonelectrical equipment
Nonelectrical equipment
Transportation Equipment
Construction
Residential Const.
One-unit Construction
Primary Metals
Construction
Construction
Residential Const.
One-unit Const.
Nonresidential Const.
Construction
Residential Const.
One-unit Const.
Nonresidential Const.
Aerospace
Transportation Equipment
Autos
Federal Defense Spending
Federal Defense Spending
Federal Defense Spending
Transportation Equipment
Autos
Nonresidential Const.
Primary Metals
Iron & Steel
Primary Metals
Iron & Steel
Basic Steel and Mills
<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>Industry Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>3567</td>
<td>Industrial Furnaces</td>
<td>Primary Metals</td>
</tr>
<tr>
<td>3624</td>
<td>Carbon and Graphite</td>
<td>Primary Metals</td>
</tr>
<tr>
<td>3662</td>
<td>Radio &amp; TV Communication Equipment</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3672</td>
<td>Electron Tubes</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3676</td>
<td>Other Electronics</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3694</td>
<td>Engine Electrical Equipment</td>
<td>Autos</td>
</tr>
<tr>
<td>3721</td>
<td>Aircraft</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3724</td>
<td>Aircraft &amp; Missile Engines &amp; Parts</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3761</td>
<td>Guided Missiles and Space Vehicles</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3764</td>
<td>Aircraft &amp; Missile Engines &amp; Parts</td>
<td>Federal Defense Spending</td>
</tr>
<tr>
<td>3825</td>
<td>Mechanical Measuring Devices</td>
<td>Electrical equipment</td>
</tr>
<tr>
<td>3843</td>
<td>Dental Equipment and Supplies</td>
<td>Federal health spending</td>
</tr>
<tr>
<td>3996</td>
<td>Hard Surface and Floor Coverings</td>
<td>Construction</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Residential Const.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>One-unit Const.</td>
</tr>
</tbody>
</table>
Appendix 2

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 paper. 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.

<table>
<thead>
<tr>
<th></th>
<th>Wages</th>
<th>Profits</th>
<th>Union</th>
<th>Concentration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full</td>
<td>Our</td>
<td>Full</td>
<td>Our</td>
</tr>
<tr>
<td></td>
<td>Sample</td>
<td>Sample</td>
<td>Sample</td>
<td>Sample</td>
</tr>
<tr>
<td>10%</td>
<td>12.22</td>
<td>14.87</td>
<td>9.76</td>
<td>10.71</td>
</tr>
<tr>
<td>30%</td>
<td>16.09</td>
<td>17.58</td>
<td>14.74</td>
<td>15.67</td>
</tr>
<tr>
<td>50%</td>
<td>18.83</td>
<td>19.94</td>
<td>19.93</td>
<td>20.19</td>
</tr>
<tr>
<td>70%</td>
<td>21.16</td>
<td>21.78</td>
<td>27.11</td>
<td>25.69</td>
</tr>
<tr>
<td>90%</td>
<td>24.67</td>
<td>25.66</td>
<td>51.40</td>
<td>38.40</td>
</tr>
</tbody>
</table>


N. Cham. P/EPGE SPE E79r
Autor: Estevão, Marcello.
Título: The role of profits in wage determination:

FGV - BMHS

000087387