A Sectoral Analysis of Price-Setting Behavior in US Manufacturing Industries*

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Abstract

In this paper we develop a mutli-sector model of firms' pricing behaviour under imperfect competition. We allow for the fact that some goods sold will be for final consumption, while others will be used as intermediate goods in further production. We assume that price setters are constrained by the existence of Calvo (1983) contracts which enables us to measure the extent of price inertia across industrial sectors. We further allow for the possibility that some firms set prices to maximise the discounted value of profits, while others set prices according to a backward-looking rule-of-thumb. We then estimate the resulting price-setting equations for 18 US manufacturing industries defined at the SIC 2-digit level over the period 1959 to 1996. We find that there is statistically significant variability in estimates of price stickiness, ranging from 4 months to almost 1.5 years with significantly more inertia in the setting of durable goods prices. We also find that estimates of backward-looking price-setting behaviour vary, with some industries acting in a purely forward-looking manner, while others are characterized by almost 50% of firms setting prices in a backward-looking fashion. Finally we find that firms in less competitive industries (characterized by higher average markup-ups) tend to adjust prices less frequently and are less likely to do so in a forward-looking manner.

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1 Introduction

The New Keynesian Phillips curve (NKPC), which links current inflation to expectations of future inflation and a measure of excess demand in the form of

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the output gap, has become a mainstay of modern macroeconomics as part of the 'New Neo-Classical Synthesis' (see Goodfriend and King (1997) for a discussion). However, until recently, this essential building block of contemporary macroeconomics has been criticized on empirical grounds (see Mankiw and Reis (2001), for example), largely because it apparently fails to capture the degree of inflation inertia many believe to be a feature of the data. Recent work on the NKPC based on Calvo's (1983) overlapping contracts framework (see for example Galí and Gertler (1999), Galí *et al.* (2001), Sbordone (2002) and Leith and Malley (2002)) suggests that, as a measure of inflationary pressures, the output gap is a poor proxy for marginal costs. Accordingly, when a theoretically coherent NKPC is estimated for the US and Euro-area, using aggregate log-linearised labor share data as a measure of marginal costs, the NKPC appears to be a reasonable model of inflation.

In this paper we build on the insight of this approach, but extend the analysis to take account of sectoral differences in price-setting behavior. Several authors have noted that monetary policy can have significantly diverse impacts on different sectors, with particular attention being paid to the varying responses to monetary policy of durable and non-durable consumer good sectors (see, for example, Galí (1993) and Baxter (1996)). Despite these differences, most analyses of optimal monetary policy undertaken as part of the New Neo-Classical Synthesis utilize single-sector models. An exception to this is Erceg and Levin (2002) who develop a two-sector sticky-price model and demonstrate that welfare depends upon inflation and output gaps within each sector, not simply aggregate variables. In Erceg and Levin (*op cit.*) the differences across sectors stem from demand-side differences across durable and non-durable goods, but a common degree of price-stickiness is assumed across sectors. Aoki (2001) also develops a sectoral model, but focuses on differences in the degree of price stickiness across sectors. His analysis suggests that monetary policy should target inflation in the sticky-price sector rather than focusing on an aggregate measure. In other words, welfare is maximized by reducing the distortions associated with price stickiness through targeting a measure of 'core' inflation which is based on inflation in the sticky price sector. Accordingly, any finding of significant asymmetries in price-setting behavior across sectors should provide evidence on which to base a 'core' measure of inflation. Additionally, Bartsky *et al.* (2003) suggest that whether or not price stickiness rests in durable or non-durable goods sectors is crucial in defining the impact of monetary policy on the economy. Finally, evidence on price changes on individual consumer goods collected by Bils and Klenow (2002) also suggests significant differences in nominal inertia across sectors. For these reasons, estimating the extent of nominal inertia across sectors is an important extension of the NKPC approach.

To allow for sectoral differences in price-setting, we assume that imperfectly competitive firms sell their goods to buyers which purchase goods from all sectors in the economy. This implies that the firms take into account the price they set relative to the prices set by other firms, both in their own industry and across the economy as a whole. Additionally, by allowing firms in one sector to buy goods from other firms (both in its sector and in other sectors) for use in production, we also allow for variations in raw materials and intermediate goods prices to affect the marginal costs faced by a price-setter.

More specifically, we construct a model of firms' price-setting behavior which allows firms to sell their products to consumers, the government and other firms, and to substitute intermediate goods for labor in production. In our setup firms will set their prices subject to the constraints implied by Calvo contracts. When firms are able to adjust prices, some will set the new price to maximize the discounted value of future profits, while others will follow a simple backward-looking rule of thumb which, although not optimal in the short-run, will achieve the profit-maximizing price in the long-run. The possible existence of rule of thumb price setters may reflect information processing costs along the lines of Sims (1998) and allows us to measure the extent of backward-looking behavior in price setting. Our formulation gives rise to a specification of the NKPC at the sectoral level.

When we econometrically estimate our specification of price-setting behavior for the US manufacturing industries at the 2-digit level, we find plausible estimates of the degree of inertia in each sector. Moreover these results suggest that price setting in durable goods industries is more sticky than in non-durable goods industries. Our econometric work also suggests that the majority of firms set prices optimally, in a forward-looking manner, rather than following backward-looking rules of thumb. It also appears to be the case that firms with more market-power (as measured by the mark-up) adjust prices less frequently than firms in more competitive industries. They are also more likely to follow simple backward-looking rules of thumb when they do adjust price. Additionally, as one would expect, the variability of output (inflation) is positively (negatively) correlated with our estimate of price stickiness. Finally, our results imply that there are significant asymmetries in the degree of price-stickiness among industrial sectors as well as asymmetries in the degree of backward-looking behavior in price setting, which as pointed out above may be a cause for concern for policy makers in the Fed.

The rest of the paper is organized as follows. In section 2 we discuss the importance of materials/intermediate goods costs to manufacturing firms. In Section 3 we derive our sectoral NKPCs in the presence of intermediate/material good inputs. In Section 4 we estimate the model for 18 2-digit US manufacturing industries. Section 5 contains our conclusions.

2 Intermediate Inputs in US Manufacturing

The importance of material costs within US manufacturing industries is highlighted in Table 1 which gives, along with other descriptive statistics, average values between 1958 and 1996 for the ratio of production worker wage costs, $W^i * H^i$ to variable costs (defined as wage costs plus material costs, $P^{m,i} * m^i$). The table also details the average ratio of production worker wage costs to gross output, $P^i * y^i$ and the ratio of material costs to gross output. The final column calculates the price-cost mark-up implicit in each industry as $\frac{\text{Value Added - Production Worker Payroll}}{\text{Value Added+Cost of Materials}}$, following Domowitz *et al.* (1988).

Table 1 - Mark-up & Costs in US Manufacturing Industries[1]

SIC Code	$\frac{W^i*H^i}{W^i*H^i+P^{m,i}*m^i}$	$\frac{W^i*H^i}{P^i*y^i}$	$\frac{P^{m,i}*m^i}{P^i*y^i}$	Markup
Agg. Manufacturing	0.169	0.115	0.682	0.319
20	0.085	0.063	0.673	0.265
21	0.090	0.071	0.717	0.234
22	0.205	0.155	0.598	0.246
23	0.261	0.185	0.519	0.304
24	0.221	0.168	0.590	0.251
25	0.279	0.187	0.482	0.333
26	0.178	0.121	0.557	0.317
27	0.302	0.154	0.350	0.500
28	0.116	0.064	0.485	0.450
29	0.029	0.025	0.831	0.141
30	0.235	0.152	0.493	0.355
31	0.259	0.180	0.512	0.306
32	0.266	0.163	0.450	0.384
33	0.172	0.128	0.617	0.247
34	0.248	0.165	0.499	0.334
35	0.242	0.145	0.462	0.388
37	0.160	0.114	0.595	0.287
39	0.247	0.154	0.465	0.386

>From the first three columns in Table 1 it is clear that material/intermediate goods costs are a far more significant part of variable costs than labor costs for all the 2-digit manufacturing industries considered in the table. This suggests that failing to take account of the impact of changes in materials prices on marginal costs may lead to a serious misspecification of estimated price-setting equations. To illustrate the potential importance of this misspecification we estimate a reduced form NKPC of the following form,

$$\widehat{\pi}_t = \alpha_1 E_t \widehat{\pi}_{t+1} + \alpha_2 \widehat{MC}_t + \varepsilon_t \tag{1}$$

[1] The data used in this table are fully described in Appendix 1. Note that data limitations prevent the use of industries 36 and 38 (see Appendix 1 for SIC definitions and further detail on sources and methods).

using aggregate US manufacturing. We estimate[2] this using three alternative measures of marginal cost: (1) the output gap, (2) the ratio of production worker payroll costs to gross output and (3) the ratio of labor plus material costs to gross output.

The results of this estimation using the traditional output gap measure of marginal costs are given by,

$$\widehat{\pi}_t = \underset{(4.315)}{1.501} E_t \widehat{\pi}_{t+1} - \underset{(-1.381)}{0.105} \widehat{MC}_{1t} + \varepsilon_{1t}. \tag{2}$$

Here there is the usual problem that the coefficient on the output gap is both statistically insignificant and wrongly-signed (see Galí *et al.* (2001) for a discussion in the context of aggregate US and Euro-area data). The coefficient on expected inflation is also in excess of one. If we replace the output gap measure of marginal costs with the detrended ratio of production worker payroll cost to gross output[3], the estimates become,

$$\widehat{\pi}_t = \underset{(11.264)}{1.03881} E_t \widehat{\pi}_{t+1} - \underset{(-2.977)}{0.105} \widehat{MC}_{2t} + \varepsilon_{2t}. \tag{3}$$

In this case, the coefficient on the 'marginal cost' measure is not only wrongly-signed it is also statistically significant. It appears that the usual labor share measure does not work in the case of US manufacturing industries. Finally, we run the same regression but replace our measure of marginal costs with the ratio of production workers' payroll plus intermediate inputs relative to gross output[4]. The estimates are as follows,

$$\widehat{\pi}_t = \underset{(8.988)}{0.998} E_t \widehat{\pi}_{t+1} + \underset{(2.288)}{0.138} \widehat{MC}_{3t} + \varepsilon_{3t}. \tag{4}$$

Now the coefficients on inflation and the marginal cost measure are of the correct sign and magnitude, as well as being statistically significant. This section therefore suggests not only that intermediate goods are a significant part of manufacturing firms' variable costs, but that failing to take account of this fact implies that estimates of price inertia based on the NKPC may be significantly biased.

[2] The reduced-form NKPC is estimated using Hansen's (1982) Generalised Method of Moments (GMM), with four lags of output price inflation, commodity price inflation and a constant term as instruments. All data have been quadratically detrended to reflect the non-linear trends present in both the industry level inflation and marginal cost data. The estimated standard errors, reported in brackets, are robust to both serial correlated and heteroscedastic errors. When calculating the *HAC* covariance matrix of sample moments we use a value of four for the lag truncation parameter. The results reported above are also robust to alternative values of this parameter ranging from 2 to 12.

[3] This is slightly different from the labour share variable used in aggregate studies in two ways. Firstly it is based only on production workers and secondly, these are measured relative to gross output, rather than a value-added definition of output. The theory derived in Section 3 below, will show this to be the appropriate measure.

[4] This measure is intended to be a proxy for marginal costs when material costs are important. Section 3 will, however, develop a more theoretically coherent measure which will be employed in the structural estimation of Section 4.

3 The Model

In this section we analyze a model of firms' price setting behavior which takes account of the sectoral composition of the domestic economy and allows a significant role for material/intermediate goods costs in the determination of firms' marginal costs. To do so we assume that imperfectly competitive firms sell their goods to buyers which purchase goods from all sectors in the economy. This implies that the firms take into account the price they set relative to the prices set by other firms, both in their own industry and across the economy as a whole. We further assume that firms face the constraints in price-setting implied by the use of Calvo (1983) contracts, in that they can only change their prices after a random interval of time. Within this constraint, we also allow firms to adopt two forms of price-setting behavior. Some firms set prices by maximizing the expected discounted value of future profits, while the remaining firms choose to follow a simple rule of thumb which updates their prices in line with inflation and the price changes they observed in the previous period.

3.1 Product Demand

We first turn to consider the demand for the firm's product. There are N sectors in the economy. We allow for the possibility that goods produced in one sector are not identical in the impact they have on utility. Specifically, we assume that consumers maximize the utility generated by consumption of CES bundles of goods produced by each sector,

$$c(i)_t^j = \left[\int_0^1 (c(i,z)_t^j)^{\frac{\theta_i - 1}{\theta_i}} dz \right]^{\frac{\theta_i}{\theta_i - 1}}. \qquad (5)$$

where, $c(i)_t^j$ is a CES index of consumer goods produced in sector i consumed by consumer j. We do not specify the exact way in which these bundles produced by different sectors enter utility. However, it should be borne in mind that there is an implicit model of utility maximization which allocates an individual's consumption spending across time. This can be the usual consumption Euler equation or can include more complex dynamics, such as those arising from habits effects as in Leith and Malley (2002) or the possibility that some goods are durable, as in Erceg and Levin (2002). However, in analyzing firms' pricing decisions we only require knowledge of how consumers, the government and other firms allocate their spending across firms within a given sector, not how the spending is allocated across time. The price index associated with the goods produced in sector i is defined as,

$$P_t^i = \left[\int_0^1 p_t(i,z)^{1-\theta_i} dz \right]^{\frac{1}{1-\theta_i}}. \qquad (6)$$

where $p_t(i,z)$ is the price set by firm z in sector i at time t.

We also assume that firms demand goods for use in production and $m_t^{i,z}$ is a CES aggregate of the intermediate goods produced by other firms and used in firm z of sector i's production function,

$$m_t^{i,z} = \left[\sum_{n=1}^{N} \left(\varkappa_n^i\right)^{\frac{1}{\gamma_i}} \left(m(n)_t^{i,z}\right)^{\frac{\gamma_i - 1}{\gamma_i}} \right]^{\frac{\gamma_i}{\gamma_i - 1}}. \tag{7}$$

Note that the parameterization of the CES aggregate is sector specific. Accordingly we can also define a price index associated with the use of intermediate goods in production in sector i,

$$P_t^{m,i} = \left[\sum_{n=1}^{N} \varkappa_n^i \left(P_t^n\right)^{1-\gamma_i} \right]^{\frac{1}{1-\gamma_i}}. \tag{8}$$

The demand for goods produced in sector i for use in production is given by,

$$m(i)_t = \sum_{n=1}^{N} \varkappa_n^i \left(\frac{P_t^n}{P_t^{m,n}} \right)^{-\gamma_n} m_t^n \tag{9}$$

where we sum across each sector's demand for intermediate goods produced in sector i. Accordingly, the demand for firm z's product within sector i is given by,

$$y(i,z)_t = \left(\frac{p_t(i,z)}{P_t^i} \right)^{-\theta_i} \left(c(i)_t + g(i)_t + m(i)_t\right) \tag{10}$$

where $m(i)_t$ is the demand for the basket of products produced in sector i for use as an intermediate good in the production of all firms in the economy. This demand is obtained from integrating across the demands of individual firms, defined as $m(i)_t^j = \left[\int_0^1 \left(m(i,z)_t^j\right)^{\frac{\theta_i - 1}{\theta_i}} dz \right]^{\frac{\theta_i}{\theta_i - 1}}$ in the case of firm j, where $m(i,z)_t^j$ is that part of that part of firm j's demand allocated to firm z within sector i. Note that we do not impose the same degree of substitutability between sectoral output when used for consumption rather than production. Accordingly the aggregate consumer price level may differ from the index of intermediate goods prices. The demand for the firm's product depends upon its price relative to the prices of other producers in its sector, as well as the amount of public and private consumption and intermediate goods demand allocated to each sectors' goods where these proportions depend on the relative prices between sectors and the specification of the consumers' utility function and the governments' objective function. Therefore, we are allowing for substitution in demand between intra- and inter-sectoral goods, in describing the demand for sector i's representative firm's product.

3.2 Defining Marginal Cost

We now turn to consider the form of the firm's production function. We assume that firms combine capital, intermediate goods and labor in producing their output,

$$y(i,z)_t = \left(\alpha_{H,i} H(i,z)_t^{\frac{\rho_i - 1}{\rho_i}} + \alpha_{m,i} (m_t^{i,z})^{\frac{\rho_i - 1}{\rho_i}} \right)^{\frac{\rho_i}{\rho_i - 1}/\psi_i} \overline{K}_i^{1-\frac{1}{\psi_i}} \tag{11}$$

where $H(i,z)_t$ is the quantity of labor of workers of type i used in production by firm z and $m_t^{i,z}$ is a CES aggregate of the intermediate goods produced by other firms and used in firm z of sector i's production function,

$$m_t^{i,z} = \left[\sum_{n=1}^{N} (\varkappa_n)^{\frac{1}{\gamma_i}} (m(n)_t^{i,z})^{\frac{\gamma_i - 1}{\gamma_i}} \right]^{\frac{\gamma_i}{\gamma_i - 1}}. \tag{12}$$

We model all these inputs as imperfect substitutes and ρ_i measures the elasticity of substitution between them. Firms also possess a stock of capital, $\overline{K}_i$, which is assumed, for simplicity, to be fixed and $1 - \frac{1}{\psi_i}$ describes the weight given to capital in production.

Here the first-order conditions for cost minimization together reveal the cost-minimizing combination of labor and intermediate goods used in production,

$$\left(\frac{H(i,z)_t}{m_t^{i,z}} \right) = \left(\frac{W_t^i}{P_t^{m,i}} \frac{\alpha_{m,i}}{\alpha_{H,i}} \right)^{-\rho_i}. \tag{13}$$

This can then be substituted back into the production function to obtain,

$$H(i,z)_t = (y(i,z)_t)^{\psi_i} \left(\alpha_{H,i} + \alpha_{m,i} \left(\frac{W_t^i}{P_t^{m,i}} \frac{\alpha_{m,i}}{\alpha_{H,i}} \right)^{\rho_i - 1} \right)^{\frac{-\rho_i}{\rho_i - 1}} \overline{K}_i^{1-\psi_i} \tag{14}$$

and,

$$m_t^{i,z} = (y(i,z)_t)^{\psi_i} \left(\alpha_{H,i} \left(\frac{W_t^i}{P_t^{m,i}} \frac{\alpha_{m,i}}{\alpha_{H,i}} \right)^{1-\rho_i} + \alpha_{m,i} \right)^{\frac{-\rho_i}{\rho_i - 1}} \overline{K}_i^{1-\psi_i}. \tag{15}$$

We can next consider the definition of real marginal cost for firm z in sector i,

$$MC(i,z)_t = \frac{W_t^i}{P_t} \frac{\partial H(i,z)_t}{\partial y(i,z)_t} + \frac{P_t^{m,i}}{P_t} \frac{\partial {m^{i,z}}_t}{\partial y(i,z)_t} \tag{16}$$

and after substituting for $\frac{\partial H(i,z)_t}{\partial y(i,z)_t}$ and $\frac{\partial m_t^{i,z}}{\partial y(i,z)_t}$ (from equations 14 and 15) we can decompose marginal cost into two elements - one which is independent of the firm's actions and the other which depends upon the position they are operating on their production function, such that marginal cost equals,

$$\begin{aligned} MC(i,z)_t &= (y(i,z)_t)^{\psi_i - 1} \left[\begin{array}{c} \frac{W_t^i}{P_t}\left(\alpha_{H,i} + \alpha_{m,i}\left(\frac{W_t^i}{P_t^{m,i}}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i - 1}\right)^{\frac{-\rho_i}{\rho_i - 1}} \\ +\frac{P_t^{m,i}}{P_t}\left(\alpha_H\left(\frac{W_t^i}{P_t^{m,i}}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{1-\rho} + \alpha_{m,i}\right)^{\frac{-\rho_i}{\rho_i - 1}} \end{array} \right] \psi_i \overline{K}_i^{1-\psi_i} \\ &= (y(i,z)_t)^{\psi_i - 1}\widetilde{MC}_t^i. \end{aligned} \quad (17)$$

The first multiplicative term captures the increase in firm specific marginal costs through increasing production given the fixed stock of capital[5] and decreasing marginal returns to the remaining factors. The second element reflects the labor costs that enter into the costs of production and are constant across firms in the sector. We label this second term, $\widetilde{MC}_t^i$.

3.3 Profit Maximizing Price Setting

We can now start to consider the problem facing a firm which chooses to set its price in order to maximize profits. The real variable profits[6] (deflated by the general price index, since the firms are assumed to be owned by consumers who all face the same form of consumption bundle) in period t of the firm producing good z in sector i are given by

$$\frac{p(i,z)_t}{P_t}y(i,z)_t - \frac{W_t^i}{P_t}H(i,z)_t - \frac{P_t^{m,i}}{P_t}m_t^{i,z}. \quad (18)$$

We also allow for the possibility that labor markets are sector specific, such that W_t^i is the wage rate applicable to sector i, although there may be significant labor flows between sectors acting to equate wage rate, *ceteris paribus*. Such firms are able to change their price with probability α_i in a given period, so that $\frac{1}{1-\alpha_i}$ measures the length of time a price contract is expected to exist. This allows us to write the problem facing a firm which is able to change prices

[5] An alternative modelling strategy would be to allow capital to be reallocated across firms so as to equate the shadow value of capital, implying that each firm's marginal cost is identical to the economy-wide average cost (see Sbordone (2002) for a discussion). However, the possibility that firms can reallocate capital without friction, but cannot reset prices continuously seems implausible.

[6] We ignore the fixed costs of utilising the capital stock in formulating the firm's problem and we assume that all shocks are sufficiently small that firms continue to earn positive profits at all points in time. Accordingly, the definition of labour we are considering here is production workers. For simplicity we assume that other workers payroll costs contribute to overheads which can be thought of as an element of fixed costs.

in period t as,

$$\begin{aligned} & \left(\frac{x_t^i}{P_t^i}\right)^{-\theta_i}(c_t^i+g_t^i+m_t^i)\frac{x_t^i}{P_t} \\ & -\widetilde{MC}_t^i\left(\frac{x_t^i}{P_t^i}\right)^{-\theta_i\psi_i}(c_t^i+g_t^i+m_t^i)^{\psi_i} \\ & +E_t\sum_{s=1}^{\infty}\frac{(\alpha_i)^s\left[\begin{array}{c}\left(\frac{x_t^i}{P_{t+s}^i}\right)^{-\theta_i}(c_{t+s}^i+g_{t+s}^i+m_{t+s}^i)\frac{x_t^i}{P_{t+s}} \\ -\widetilde{MC}_{t+s}^i\left(\frac{x_t^i}{P_{t+s}^i}\right)^{-\theta_i\psi_i}(c_{t+s}^i+g_{t+s}^i+m_{t+s}^i)^{\psi_i}\end{array}\right]}{\prod_{j=1}^{s}r_{t+j-1}}. \end{aligned} \tag{19}$$

Here profits are discounted at the gross real rate of interest, r_t. Due to the ability of consumers to hold diversified portfolios and thereby pool the risks associated with staggered price setting (the only source of risk formally modelled) this discount factor will be the same across firms. The first order condition for this optimization is given by,

$$(x_t^i)^{1+\theta_i(\psi_i-1)}=\frac{\begin{array}{c}\psi_i\theta_i(P_t^i)^{\psi_i\theta_i}\widetilde{MC}_t^i(c_t^i+g_t^i+m_t^i)^{\psi_i} \\ +E_t\sum_{s=1}^{\infty}\frac{(\alpha_i)^s(\theta_i\psi_i(P_{t+s}^i)^{\psi_i\theta_i}\widetilde{MC}_{t+s}^i(c_{t+s}^i+g_{t+s}^i+m_{t+s}^i)^{\psi_i})}{\prod_{j=1}^{s}r_{t+j-1}}\end{array}}{\begin{array}{c}(\theta_i-1)(P_t^i)^{\theta_i}P_t^{-1}(c_t^i+g_t^i+m_t^i) \\ +E_t\sum_{s=1}^{\infty}\frac{(\alpha_i)^s(\theta_i-1)(P_{t+s}^i)^{\theta_i}P_{t+s}^{-1}(c_{t+s}^i+g_{t+s}^i+m_{t+s}^i)}{\prod_{j=1}^{s}r_{t+j-1}}\end{array}}. \tag{20}$$

The first-order condition for the optimal price can be log-linearised to yield,

$$\begin{aligned} (\frac{(1+\theta_i(\psi_i-1))\overline{r}}{\overline{r}-\alpha_i})\widehat{x}_t^i &= \widehat{\widetilde{MC}}_t^i+(\psi_i-1)\widehat{y}_t^i+\widehat{P}_t+\theta_i(\psi_i-1)\widehat{P}_t^i \\ & +\sum_{s=1}^{\infty}(\frac{\alpha_i}{\overline{r}})^s E_t[\widehat{\widetilde{MC}}_{t+s}^i+(\psi_i-1)\widehat{y}_{t+s}^i \\ & +\widehat{P}_{t+s}+\theta_i(\psi_i-1)\widehat{P}_{t+s}^i] \end{aligned} \tag{21}$$

where $y_t=c_t^i+g_t^i+m_t^i$ is the average firm's gross output supplying, private and public demand. This infinite forward summation, can also be quasi-differenced to give a first order difference equation describing the evolution of the optimal price set by profit-maximizing firms,

$$(\frac{\alpha_i}{\overline{r}-\alpha_i})E_t\widehat{x}_{t+1}^i=(\frac{\overline{r}}{\overline{r}-\alpha_i})\widehat{x}_t^i-\widehat{\widetilde{MC}}_t^i-(\psi_i-1)\widehat{y}_t^i-\widehat{P}_t-\theta_i(\psi_i-1)\widehat{P}_t^i. \tag{22}$$

The firms which do not perform this optimization, instead follow a rule of thumb whereby they set a price equal to the average price set on the previous period after scaling this up by the rate of inflation observed in the previous period. Therefore, the log-linearised index of output prices in sector i is given by,

$$\widehat{P}_t^i=\alpha_i\widehat{P}_{t-1}^i+(1-\alpha_i)\widehat{p}_t^{i,r} \tag{23}$$

where $p_t^{i,r}$ is the average reset price in sector i in period t and is given by,

$$\widehat{p}_t^{i,r} = (1-\omega_i)\widehat{x}_t^i + \omega_i \widehat{p}_t^{i,b} \tag{24}$$

ω_i is the proportion of firms following the rule of thumb, and $p_t^{i,b}$ is the price set set according to the rule of thumb,

$$\widehat{p}_t^{i,b} = \widehat{p}_{t-1}^{i,r} + \widehat{\pi}_{t-1}^i. \tag{25}$$

Substituting equation (25) into (24) gives,

$$\widehat{p}_t^{i,r} = (1-\omega_i)\widehat{x}_t^i + \omega_i \widehat{p}_{t-1}^{i,r} + \omega_i \widehat{P}_{t-1}^i - \omega_i \widehat{P}_{t-2}^i. \tag{26}$$

Inserting equation (23) into this expression then yields,

$$\begin{aligned} \frac{\widehat{P}_t^i}{1-\alpha_i} - \frac{\alpha_i \widehat{P}_{t-1}^i}{1-\alpha_i} &= (1-\omega_i)\widehat{x}_t + \omega_i \left(\frac{\widehat{P}_{t-1}^i}{1-\alpha_i} - \frac{\alpha_i \widehat{P}_{t-2}^i}{1-\alpha_i} \right) \\ &\quad + \omega_i \widehat{P}_{t-1}^i - \omega_i \widehat{P}_{t-2}^i. \end{aligned} \tag{27}$$

This can be rearranged in terms of $\widehat{x}_t^i$, substituted into equation (25) and solved using the definition of output price inflation in sector i, $\widehat{\pi}_t^i = \widehat{P}_t^i - \widehat{P}_{t-1}^i$ to give,

$$\begin{aligned} \widehat{\pi}_t^i &= \frac{\beta\alpha_i}{\lambda_i} E_t \widehat{\pi}_{t+1}^i + \frac{\omega_i}{\lambda_i}\widehat{\pi}_{t-1}^i + \frac{(1-\omega_i)(1-\alpha_i)(1-\alpha_i\beta)}{(1+(\psi_i-1)\theta_i)\lambda_i}(\widehat{MC}_t^i \\ &\quad +(\psi_i-1)\widehat{y}_t^i + \widehat{P}_t - \widehat{P}_t^i) \end{aligned} \tag{28}$$

where $\lambda_i = \omega_i + \beta\omega_i\alpha_i + \alpha_i - \omega_i\alpha_i$ and

$$\begin{aligned} \widehat{MC}_t^i &= \frac{\overline{w}^i}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}\right)}(\widehat{W}_t^i - \widehat{P}_t) \\ &\quad + \frac{\frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}\right)}(\widehat{P}_t^{m,i} - \widehat{P}_t) \end{aligned} \tag{29}$$

where $\overline{w}^{i,m} = \frac{\overline{W}^i}{\overline{P}^{m,i}}$ and $\overline{w}^i = \frac{\overline{W}^i}{\overline{P}}$. In other words, marginal costs depend upon the price of labor, $\widehat{W}_t^i - \widehat{P}_t$ and the price of materials/intermediate goods for use in production, $\widehat{P}_t^{m,i} - \widehat{P}_t$ as well as the extent of diminishing marginal returns to these two inputs when capital is fixed in the short–run, which is captured by $(\psi_i - 1)\widehat{y}_t^i$.

Appendix 2 then details the transformation of this specification into a form which is appropriate for estimation,

$$
\begin{aligned}
\widehat{\pi}_t^i &= \frac{\beta\alpha_i}{\lambda_i}E_t\widehat{\pi}_{t+1}^i + \frac{\omega_i}{\lambda_i}\widehat{\pi}_{t-1}^i + \frac{(1-\omega_i)(1-\alpha_i)(1-\alpha_i\beta)}{(1+(\psi_i-1)\theta_i)\lambda_i}(\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i+\overline{P}^{m,i}\overline{m}^i}\widehat{s}_t^i \\
&\quad +\rho_i\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i+\overline{P}^{m,i}\overline{m}^i}(1-\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i+\overline{P}^{m,i}\overline{m}^i})\widehat{w}_t^{i,m} \qquad (30) \\
&\quad +(1-\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i+\overline{P}^{m,i}\overline{m}^i})(\widehat{P}_t^{m,i}-\widehat{P}_t^i+(\psi_i-1)\widehat{y}_t^i).
\end{aligned}
$$

where $\widehat{s}_t^i = \widehat{W}_t^i - \widehat{P}_t^i + \widehat{H}_t^i - \widehat{y}_t^i$ is the deviation of the ratio of labor costs to gross output, $\widehat{w}_t^{i,m} = \widehat{W}_t^i - \widehat{P}_t^{i,m}$ is the wage rate deflated by the price of materials in industry i, $\widehat{P}_t^{m,i} - \widehat{P}_t^i$ are the price of materials deflated by the output price of industry i and $\widehat{y}_t^i$ is gross output. We respecify the Phillips curve in this way, to make it comparable to existing studies which focus on the labor share variable, $\widehat{s}_t^i$ and to allow estimation of the elasticity of substitution between intermediate goods and labor in production, ρ_i. If no intermediate goods are used in production then this reduces to the Phillips curve employed in, for example, Galí *et al.* (2001) and Leith and Malley (2002, 2003). However, as we saw in Table 1, at the sectoral level, material inputs are a major source of costs which should be accounted for in the firm's pricing decision.

4 Estimation and Empirical Results

In this Section we jointly estimate the parameters of the model derived in Section 2 for 18 2-digit manufacturing industries over the period 1958(2) to 1996(3)[7]. This implies the estimation of 109 parameters (i.e. 5x18+1 'deep' parameters and 1x18 steady-state ratios) with only 150 observations. To reduce this problem to more manageable dimensions we first calibrate θ_i, ψ_i and the steady-state ratio of production worker payroll to variable costs, $\frac{W^i*H^i}{W^i*H^i+P^{m,i}*m^i}$ (see Table 1) since these are readily identifiable from the data[8].This is also the general approach adopted in much of the literature estimating Phillips curves using aggregate data (see, for example, Galí *et al.* (2001)) where ψ_i is typically inferred from labor-share data and the mark-up is based upon survey evidence and/or cited empirical studies.

Under imperfect competition the above parameters are calibrated as follows

[7]Note that all of the data employed in the estimation of our NKPCs are seasonally adjusted and that industries 36 and 38 had to be dropped due to insufficient observations for W. Further detail on data availability are reported in Appendix 1.

[8]Note that we use the mean value of these parameters and the steady-state ratio over the estimation period. Further note that all of the estimations reported below are robust to alternative values of these parameters, e.g. median values, end of sample values and various weighted averages. These results are not reported here to preserve space but will be made available on request.

$$\theta_i = \frac{(1+\mu_i)}{\mu_i} \tag{31}$$

where μ_i is the mark-up for each industry (see Table 1) and

$$\psi_i = \frac{1+\mu_i}{\frac{\overline{W}^i\overline{H}^i+\overline{P}^{m,i}\overline{m}^i}{\overline{P}^i\overline{y}^i}}. \tag{32}$$

where $\frac{\overline{W}^i\overline{H}^i+\overline{p}^{m,i}\overline{m}^i}{\overline{P}^i\overline{y}^i}$ is the labor and intermediate goods share (can also be implied from Table 1).

Moreover, conditioning on these relatively well known parameters allows us to concentrate on the estimating the remaining 55 parameters. These parameters include firms' steady-state discount factor, β, the probability that a firm in sector i can reset their price in period t, α_i, the proportion of firms following rule of thumb pricing behavior in time t, ω_i and the parameter measuring the elasticity of substitution between labor and imported intermediate goods, ρ_i for each industry. We compare the estimates across sectors and this allows us to draw a number of conclusions of direct relevance to policy makers.

4.1 Empirical Considerations and Estimator

Given that our model incorporates forward looking rational expectations (RE), we employ Hansen's (1982) generalized method of moments (GMM) estimator which easily handles the set of orthogonality conditions suggested by the RE hypothesis[9]. To illustrate how we apply GMM to obtain parameter estimates and specification consistent standard errors, consider the following system of nonlinear equations given by the 18 sectoral NKPCs characterized by (30),

$$\mathbf{y}_t = \mathbf{f}(\boldsymbol{\theta}, \mathbf{x}_t) + \mathbf{u}_t \tag{33}$$

where $\mathbf{y}_t$ is a (18x1) vector of dependent variables, $\left[\widehat{\pi}_t^{20}, \widehat{\pi}_t^{21}, ...\widehat{\pi}_t^{39}\right]'$ ordered by SIC-code; $\boldsymbol{\theta}$ is the (55x1) vector of unknown parameters, $[\boldsymbol{\theta}_{20}(=\alpha_{20}, \omega_{20}, \beta, \rho_{20})$ $;...\boldsymbol{\theta}_{39}(=\alpha_{39}, \omega_{39}, \beta, \rho_{39})]'$; $\mathbf{x}_t$ is the (72x1) vector of explanatory variables, $[x_{20t}(=\widehat{\pi}_{t+1}^{20}, \widehat{\pi}_{t-1}^{20}, (\widehat{s}_t^{20}, \widehat{y}_t^{20}, \widehat{P}_t^{m,20} - \widehat{P}_t^{20}), \widehat{w}_t^{20,m}); x_{21t}, ..., x_{39t})]'$[10];and $\mathbf{u}_t$ is the (18x1) vector of errors $[u_t^{20}, ...u_t^{39}]'$.

The r orthogonality conditions for our model can be written as follows

[9] Although several recent papers question the roubustness of GMM in this context (see Rudd and Whelan (2002) and Lindé (2003)), the paper by Galí *et al.*, 2003 convincingly refutes these claims.

[10] Note that calibrating θ_i, ψ_i, and $\frac{W^i * H^i}{W^i * H^i + P^{m,i} * m^i}$, using the data, serves to combine several elements of marginal cost via a linear combination of $\widehat{s}_t^i, \widehat{y}_t^i, \widehat{P}_t^{m,i} - \widehat{P}_t^i$ which explains why all 3 pieces of data are treated as one variable (in brackets).

$$\mathbf{h}(\boldsymbol{\theta}, \mathbf{w}_t) = \begin{bmatrix} E_t[y_{20t} - f_{20}(\boldsymbol{\theta}, \mathbf{x}_t)]\mathbf{z}_t = 0 \\ \cdot \\ \cdot \\ E_t[y_{39t} - f_{39}(\boldsymbol{\theta}, \mathbf{x}_t)]\mathbf{z}_t = 0 \end{bmatrix} \tag{34}$$

where $f_i(\boldsymbol{\theta}, \mathbf{x}_t)$ denotes the i^{th} element of $\mathbf{f}(\boldsymbol{\theta}, \mathbf{x}_t)$; $\mathbf{w}_t \equiv (\mathbf{y}'_t, \mathbf{x}'_t, \mathbf{z}'_t)'$; $\mathbf{z}_t$ is a (5x1) vector of instruments $[\widehat{\pi}_{t-1}, \widehat{s}_{t-1}, \widehat{y}_{t-1}, \widehat{\pi}^c_{t-1},$ *constant term*$]'$; $\widehat{\pi}$, $\widehat{s}$, $\widehat{y}$ refer to aggregate manufacturing detrended inflation, labor's share and output respectively and $\widehat{\pi}^c$, to commodity price inflation. Finally we assume that $E_t(\mathbf{z}_t, \mathbf{u}_t) = 0$. Further note that all hatted variables are calculated as deviations away from a quadratic trend[11].

Given the above setup we obtain the GMM estimate of the unknown parameter vector $\boldsymbol{\theta}$ as the value that minimizes

$$Q = (\boldsymbol{\theta}; \mathbf{Y}_T) = \left[(1/T)\sum_{t=1}^{T} \mathbf{h}(\boldsymbol{\theta}, \mathbf{w}_t)\right]' \widehat{S}_T^{-1} \left[(1/T)\sum_{t=1}^{T} \mathbf{h}(\boldsymbol{\theta}, \mathbf{w}_t)\right] \tag{35}$$

where $\widehat{S}_T^{-1}$ is an estimate of the inverse of the covariance matrix of sample moments. To obtain standard errors which are robust to heteroscedasticity and autocorrelation of unknown form, we calculate $\widehat{S}$ using the Newey and West (1987) estimator,

$$\widehat{S}_T = \widehat{\Gamma}_{0,T} + \sum_{v=1}^{q} \{1 - [v/(q+1)]\}(\widehat{\Gamma}_{v,T} + \widehat{\Gamma}'_{v,T}) \tag{36}$$

where

$$\widehat{\Gamma}_{v,T} = +(1/T) \sum_{t=v+1}^{T} [\mathbf{h}(\widehat{\boldsymbol{\theta}}, \mathbf{w}_t)][\mathbf{h}(\widehat{\boldsymbol{\theta}}, \mathbf{w}_{t-v})]' \tag{37}$$

and q is the lag truncation parameter[12]. Finally to test the validity of our overidentifying restrictions we calculate Hansen's $J - statistic$ which is distributed $\chi^2(r - a)$ where r and a denote the number of orthogonality conditions and parameters respectively. For our estimation $a = 55$ and $r = 18(4+1) = 90$, i.e. 18 equations, 4 instruments plus a constant, therefore $J\tilde{}\chi^2(35)$.

4.2 Interpretation of Results

The results of estimating the system of 18 2-digit industries are detailed in Table 2. Descriptions of the industries corresponding to the SIC codes can be

[11] This reflects the non-linear trends present in both the industry level inflation and marginal cost data.

[12] In the estimations reported in Table 2, the value of q is equal to 4. Note that we use the Bartlett spectral density kernal to insure the positive definiteness of the covariance matrix of the orthogonality conditions (see Newey and West, 1987). Further note that these results are extremely robust to alternative values of q, e.g. we examined values ranging from 2 to 12. To preserve space, these results are not reported but will be made available on request.

found in Appendix 1. There are several things to note about these results. Firstly, with the exception of industries 20 and 29 (Food and Petroleum Refining, respectively) all estimates of the degree of price-stickiness are statistically significant and plausible. Of the remaining industries, the most flexible industry is 24 (Lumber and Wood Products (exc. Furniture) and the least, flexible 37 (Transportation Equipment). In most industries there is also a significant degree of backward-looking behavior, although the majority of prices are set in a profit-maximizing manner[13].

With the exception of industry 21 - Tobacco Products, which has an estimated elasticity of substitution between labor and intermediate goods of 5.99 with an associated $t - stat.$ of 3.06, the degree of substitutability between labor and intermediate goods is not significantly different from zero. A likely explanation of this result is that, at the quarterly frequency, there is little scope for meaningful substitution between labor and intermediate goods such that a Leontief production function is the most accurate description of the short-run production technology. However, it is important to note that even if $\rho_i = 0$ in a particular industry this does not remove intermediate goods from the definition of marginal costs - in fact, it simply means that there is limited scope for substitution between the two inputs being used to moderate the impact of fluctuations in labor and intermediate goods costs on marginal costs.

The final parameter estimated within the system is the discount factor which is common across firms. This has a point estimate of 0.93 with an associated $t - stat.$ of 22.2. These are in line with the estimates in Galí and Gertler (2001) using aggregate US data. While this estimate implies a discount factor which is higher than that typically assumed in specifying consumer preferences, it may simply reflect undiversifiable risk (not formally modelled in the current paper) common to US manufacturing firms.

[13]Further relationships between the estimated parameters and other stylised descriptions of each industry are discussed below.

Table 2 - Estimation Results

Sic Code	α_i	ω_i	$\left(\frac{1}{1-\alpha_i}\right)3$	adj. R^2
20	0.68 (1.42)	−0.03 (−0.42)	9.4 months	0.19
21	0.49 (5.60)	0.17 (3.52)	5.9 months	0.28
22	0.68 (7.12)	0.26 (3.75)	9.4 months	0.51
23	0.68 (16.4)	0.37 (9.66)	9.4 months	0.68
24	0.30 (4.23)	0.023 (0.06)	4.3 months	0.25
25	0.69 (22.93)	0.45 (11.82)	9.8 months	0.76
26	0.49 (10.31)	0.29 (5.05)	5.9 months	0.48
27	0.62 (9.48)	0.31 (4.91)	7.9 months	0.46
28	0.64 (20.18)	0.45 (9.91)	8.3 months	0.80
29	1.00 (0.28)	0.28 (0.45)	∞ months	0.17
30	0.67 (18.44)	0.50 (12.00)	9.1 months	0.79
31	0.60 (11.65)	0.20 (2.94)	7.5 months	0.42
32	0.71 (23.58)	0.34 (5.85)	10.3 months	0.62
33	0.67 (9.81)	0.59 (3.66)	9.1 months	0.61
34	0.69 (24.18)	0.42 (10.23)	9.7 months	0.73
35	0.77 (19.43)	0.31 (4.38)	13.0 months	0.32
37	0.82 (14.70)	0.19 (3.31)	16.7 months	0.39
39	0.70 (18.53)	0.46 (8.79)	10 months	0.76

The $J-test$ is 30.45 with a $p-value$ of 0.687. Note that application of a series of unit root tests (e.g. Dickey-Fuller, weighted symetric and Phillip-Perron) indicated that the errors for each industry were stationary. This finding was not only robust across the various tests employed but also across lag lengths chosen to conduct the test (e.g. 2 to 12). These results are not reported here to preserve space but will be made available on request.

We can also assess the extent to which these results are statistically significantly different across industries. To do so, we first compare results across durable and non-durable goods industries in Table 3.

Table 3 -Weighted Coefficient Estimates

	Aggregate (1)	Durables (2)	Non-Durables (3)	(2)-(3)
α	0.683	0.720	0.621	0.099
	(0.023)	(0.029)	(0.025)	(0.039)
ω	0.345	0.329	0.370	-0.041
	(0.037)	(0.044)	(0.033)	(0.059)
$\left(\frac{1}{1-\alpha}\right)3$	9.46	10.71	7.92	2.79

The numbers in brackets are standard errors.

Table 3 reveals that, as a general rule, prices in durable goods industries (SIC 24,25, 32-39) are more sticky than those in non-durable goods (SIC 20-23, 26-31) industries with average price contract durations of 10.7 months in durable goods industries compared with only 7.9 months in non-durable goods industries and an overall manufacturing sector average of 9.5 months[14]. The differences in these estimated probabilities of price change are also statistically significantly different, at the 1% level, across the durable/non-durable categories. This seems plausible given that production lags in durable goods industries is likely to be longer and prices may be negotiated in advance of delivery. This is, however, apparently in contrast to the frequency of price change observed across 350 consumer goods by Bils and Klenow (2002) who find no statistically-significant differences in price setting behavior across durable and non-durable sectors. However, as noted by Barsky *et al.*, consumer prices of durable goods are likely to be less sticky than producer prices (especially if goods are bundled at the producer level), such that our estimates are actually consistent with this evidence. There is less difference in the proportion of backward-looking firms in these broad categories - 33% of firms in durable goods industries are backward-looking compared with 37% in non-durable goods industries and an overall average of 35%.

We also undertake pair-wise Wald tests of the statistical significance of the difference between the average number of months it takes to adjust prices in each pair of industries. Table 4 details the results of these comparisons and shows that the majority of industry specific estimates of the extent of nominal inertia are statistically significantly different across industries. For example, the number of -3.5 months in cell (21,22) indicates that price contracts typically last for 3.5 months less in industry 21 compared to industry 22. Table 5, performs the same analysis with the estimated extent of backward-looking behavior in price-setting and finds, similarly, that there is evidence of statistically significant differences in pricing behavior across industries.

[14] Note that SIC 20 and 29 are excluded from these calculations and from those which follow in Tables 4-6 since the parameter estimates for these industries were not significantly different from zero in Table 2.

A key advantage of our sectoral approach is that we can also assess the correlations between the cross-section of estimated parameters and other relevant industry-specific data. This is done in Tables 6a-6c which computes correlation coefficients between the sectoral parameter estimates, the mark-up in each industry and the extent of output and inflation variability[15]. These correlations are also broken down into durable and non-durable goods industries. Here several interesting patterns emerge. Firstly, there is a clear positive correlation between the degree of price-stickiness and the extent of backward-looking behavior, which in turn are both positively correlated with the estimated mark-up. In other words, the less competitive an industry (as captured by the size of the mark-up) the more sticky its price-setting behavior and the less likely it is to set prices in a forward-looking manner. The positive correlation between price stickiness and mark-up is also found in the study by Bils and Klenow (2002). This is particularly true in the case of durable goods industries, where the duration of price contracts is strongly correlated with the mark-up, and where there is also a strong negative correlation between both the mark-up and price contract duration and inflation variability. Another intuitive result (which is confirmed in Bils and Klenow (*op cit.*)) is that there is a clear positive correlation between output variability and the extent of price stickiness and a negative relationship between inflation variability and price stickiness. Given the highly stylized nature of the theoretical and econometric specifications, these off-model correlations between the estimated degree of price stickiness and the variability of output and inflation are very encouraging. Finally we should note that these asymmetries across industries are likely to be of concern to monetary policy makers for the reasons discussed in the introduction.

Table 6a - Patterns in the Estimates - All Industries

	α^i	ω^i	μ^i	Var(y^i)	Var(π^i)
α^i	1				
ω^i	0.53	1			
μ^i	0.30	0.33	1		
Var(y^i)	0.42	0.33	-0.07	1	
Var(π^i)	-0.69	-0.23	-0.32	0.09	1

Table 6b - Patterns in the Estimates - Durable Goods Industries

	α^i	ω^i	μ^i	Var(y^i)	Var(π^i)
α^i	1				
ω^i	0.51	1			
μ^i	0.50	0.23	1		
Var(y^i)	0.37	0.33	-0.03	1	
Var(π^i)	-0.80	-0.31	-0.69	0.21	1

[15] Output variability is measured as the average squared deviation of the logarithm of output from a quadratic trend. Inflation variability is the same measure for inflation.

Table 6c - Patterns in the Estimates - Non-Durable Goods Industries

	α^i	ω^i	μ^i	Var(y^i)	Var(π^i)
α^i	1				
ω^i	0.57	1			
μ^i	0.24	0.53	1		
Var(y^i)	0.28	0.41	-0.03	1	
Var(π^i)	-0.57	-0.07	-0.07	-0.30	1

5 Conclusions

In this paper we developed a sectoral model of firms' pricing behavior, where imperfectly competitive firms sell their products to consumers as final goods and/or to other firms for use as intermediate goods in production. We allowed our firms to utilize labor, intermediate goods and capital in production and we assume that firms are subject to the constraints implied by Calvo (1983) contracts. This allows us to develop sectoral New Keynesian Phillips Curves, which, when estimated econometrically, yield measures of the degree of price stickiness in each industry. Our specification also discriminates between firms which set prices in a manner consistent with profit-maximization and firms which follow simpler, backward-looking, rules of thumb in adjusting the prices they set.

Estimating these Phillips curves for 18 2-digit manufacturing industries in the US over the period 1959 to 1996, yields industry-specific estimates of the average length of price contracts which range from just over 4 months to almost 1.5 years. There is statistically significant variation between industries, which implies that the sectoral response to monetary policy is likely to be quite different, with durable goods industries typically suffering from more inertia than non-durable goods industries. We also find that the majority of firms' set prices in a forward-looking manner consistent with profit-maximization. However, most industries also have a significant degree of backward-looking behavior in price-setting and this tendency is more pronounced in less competitive industries which are characterized by higher average mark-ups.

These results are of interest to policy makers for a number of reasons. The first is that significant asymmetries in price-setting behavior across industries will affect the construction of a 'core' measure of inflation, the targeting of which would minimize the distortions due to staggered price-setting behavior (see Aoki (2001)). Moreover, the fact that there appears to be significant differences in price setting behavior across durable and non-durable goods industries is also crucial in determining the aggregate impact of monetary policy on the economy (see Bartsky *et al.* (2003). Aside from these points, the estimates also imply significant sectoral differences in response to monetary policy which are important in and of themselves if policy makers are concerned about the composition of industrial structure.

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Appendix 1 - Data Appendix

Monthly data

Survey evidence in the US, suggests that different products are subject to quite different degrees of price stickiness. For example, Carlton (1986) finds evidence of price stickiness ranging from 4 to 13 months. Given this, we must ensure that the data used in our estimation is at least as frequent as the lowest estimate of price inertia. This rules out for example the use of annual data since $1/(1-\alpha)$, i.e. the average number of months that prices remained fixed, would be constrained to be no less than one year.

Given the above, to estimate the NKPC developed in the theory requires that we employ data with a minimum of a quarterly frequency for the following variables: real gross output, y^i; implicit gross output deflator, P^i; number of production worker hours hours, H^i; average hourly production worker wage, W^i; number of production workers, N^i; real intermediate inputs, m^i and the implicit price deflator for intermediate inputs, $P^{m,i}$. Unfortunately, data at the 2-digit SIC level for the above variables are only available for W^i at the monthly frequency from the Bureau of Labor Statistics (BLS), Employment, Hours and Earnings (EHE). Whilst the BLS also reports monthly employment and prices on a sub-aggregate manufacturing basis there are several problems with these measures in the context of our research. First the employment data is for total and not production workers and second the producer price indices are not the correct conceptual match for the gross output deflator nor are they provided in the desired industry breakdown. For example, these data are only reported on a SIC basis from the mid-1980's. The longer historical time-series published for producer prices are on a commodity basis. Further note that the Federal Reserve Board (FRB) monthly indices of industrial production are also not a precise match for gross output since these are value-added based indices. Finally, higher frequency industry level data (i.e. quarterly or monthly) for intermediate inputs and their corresponding prices is simply not available.

Annual Data

The data provided in the National Bureau of Economic Research (NBER) Productivity Database has the major advantage that its measures provide an exact match with the requirements of the theory. However, its main disadvantage, as discussed above, is that we require at least quarterly data to undertake meaningful estimation of the NKPC. Since we have higher frequency data for W^i, we need a method of distributing the annual NBER time-series for y^i, P^i, H^i, N^i, m^i, and $P^{m,i}$ across higher frequency values. Here we will distribute to the quarterly frequency using a method, which relies on quarterly related series and yields best linear unbiased estimates of the missing observations (see below for a brief description of the distribution method employed).

Quarterly Data

The monthly data for W^i are converted to a quarterly frequency by averaging over all the observations within each quarter. To obtain estimates for the remaining data we employ a procedure which relies on estimating the relationship between our annual NBER data and the related quarterly series obtained from the BLS and FRB. As discussed above, whilst the measures from these sources do not provide the exact conceptual match with the theory, they will nonetheless be highly correlated with the annual measures and as such will act useful proxies for quarterly movements in the NBER data. Given there is not a one-to-one mapping between the series measured by BLS/FRB and the NBER data it is clearly preferable to use the former data to proxy missing quarterly movements in the NBER data instead of employing these data as direct proxies for the NBER annual data. Finally note that all of the quarterly data employed in the estimation of our NKPCs are seasonally adjusted and that industries 36 and 38 (see below for SIC definitions) had to be dropped due to insufficient observations for W^i (i.e. only reported from 1988Q1).

A Random Walk Model for Distributing Annual to Quarterly Observations

To estimate the unobserved quarterly movements in the annual NBER data we employ the method developed by Fernandez (1981). The Fernadez approach generalizes the model set out Chol and Lin (1971) by allowing for non-stationary errors in the linear stochastic relationship generating the missing observations. More specifically given n annual observations, for a variable $y_1^a, y_2^a, ..., y_n^a$, we will estimate quarterly values, $y_{t,1}$, $y_{t,2}$, $y_{t,3}$, $y_{t,4}$ for each $t = 1..., n$ so that the within year average of the quarterly series is equal to the observed annual value provided by the NBER, e.g.

$$y_t^a = \frac{(y_{t,1} + y_{t,2} + y_{t3} + y_{t,4})}{4}. \tag{38}$$

Moreover when estimating the quarterly values we follow Fernandez (1981) and further assume that the unobserved quarterly series follows a linear stochastic relationship with a set of k related observed quarterly series and the error term follows a random walk. For example, the stochastic relation for each quarter i of year t can be written as follows:

$$y_{t,i} = x_{t,i}^1\beta_1 + x_{t,i}^2\beta_2 + ... + x_{t,i}^k\beta_k + u_{t,i} \tag{39}$$

where $u_{t,i} = u_{t,i-1} + \varepsilon_{t,i}$.

The $4n$x1 vector $\mathbf{U} = (u_{1,1}\ u_{1,2}...\ u_{n,4})$ is assumed to have a zero mean and a covariance matrix $(\mathbf{D}'\mathbf{D})^{-1}$, where the $4n$x$4n$ $\mathbf{D}$ matrix is given by

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & 0 & . & . & . & . & 0 & 0 \\ -1 & 1 & 0 & 0 & . & . & . & . & 0 & 0 \\ 0 & -1 & 1 & 0 & . & . & . & . & 0 & 0 \\ . & . & . & . & & & & & . & . \\ . & . & . & . & & & & & . & . \\ 0 & 0 & 0 & 0 & . & . & . & . & -1 & 1 \end{bmatrix}. \tag{40}$$

Finally the errors $\varepsilon_{t,i}$ are assumed to be white noise with a zero mean and constant variance σ^2. Given these assumptions the Fernandez estimator is $BLUE$ since $var(\mathbf{U}) = (\mathbf{D}'\mathbf{D})^{-1}\sigma^2$.

To estimate the $\beta' s$ in (39) we require a nx$4n$ distribution matrix $\mathbf{B}$, .e.g

$$\mathbf{B} = (1/4)\begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & . & . & . & . & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & & & & & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & & & & . & . & . & . \\ . & . & . & . & . & . & . & . & & & & & . & . & . & . \\ . & . & . & . & . & . & . & . & & & & & . & . & . & . \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & . & . & . & . & 1 & 1 & 1 & 1 \end{bmatrix}. \tag{41}$$

If we next denote the nx1 vector of annual observations as $\mathbf{Y}^a = (y_1^a, y_2^a, ..., y_n^a)'$ and the $4n$x1 vector of unobserved quarterly observations as $\mathbf{Y} = (y_{1,1}, y_{1,2}, ..., y_{n,4})'$ then from (41) it follows that,

$$\mathbf{Y}^a = \mathbf{BY} = \mathbf{BX}\boldsymbol{\beta} + \mathbf{Bu} = \mathbf{X}^a\boldsymbol{\beta} + \mathbf{u}^a. \tag{42}$$

Based on the Chow and Lin (*op cit.*) analysis it can be easily shown that the optimal linear unbiased estimator for the unobserved higher frequency movements in $\mathbf{Y}$ is given by

$$\widehat{\mathbf{Y}} = \mathbf{X}\widehat{\boldsymbol{\beta}} + (\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}'(\mathbf{B}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}')^{-1}\widehat{U}^a \tag{43}$$

where $\widehat{\boldsymbol{\beta}} = [\mathbf{X}^{a\prime}(\mathbf{B}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}')^{-1}\mathbf{X}^a]^{-1}\mathbf{X}^{a\prime}(\mathbf{B}(D'\mathbf{D})^{-1}\mathbf{B}')^{-1}\mathbf{Y}^a$, $\mathbf{X}^a = \mathbf{BX}$ and $\widehat{U}^a = \mathbf{Y}^a - \mathbf{X}^a\widehat{\beta}$.

Principle Components of the Related Regressors

The next issue which needs to be confronted when applying the estimator given by (43) pertains to the choice of the appropriate k quarterly related regressors which make up the columns of $\mathbf{X}$. As discussed above, since the available higher frequency BLS/FRB data is not an exact match with the measures required by the theory and in some case with the required industry breakdown, we need to make use of an extended information set in an effort to maximize the fit with our annual NBER measures. For example, to distribute N^i to a quarterly frequency there are 24 employment related variables available from the BLS. The BLS also provides another 21 hours related variables to distribute H^i and 43 producer prices to distribute $P^i$and $P^{m,i}$. Finally, the FRB provides

23 industrial production indices which we will use to distribute y^i and m^i. A full description of these variables and their sources is given below. The obvious advantage of having access to such a large set of related regressors for each variable is that they will not only capture within industry correlations but also the cross industry correlations arising from underlying complementarities and substitutabilities in production. The disadvantage however is that it is impossible to know *apriori* which regressors to include and which to exclude. Variable exclusion is necessary to conserve degrees of freedom and to avoid the problems associated with multicollinearity.

To reduce the dimensionality of our various related regressor sets we apply the technique of principal components. For example, the regression given by (42) above can be transformed as follows

$$\mathbf{Y}^a = \mathbf{BX}\boldsymbol{\beta} + \mathbf{Bu} = (\mathbf{BXP})(\mathbf{P}'\boldsymbol{\beta}) + \mathbf{Bu} = \mathbf{BZ}\boldsymbol{\theta} + \mathbf{Bu} \tag{44}$$

where $\mathbf{Y}^a$ is an annual nx1 vector from the NBER dataset; $\mathbf{BX}$ $(= \mathbf{X}^a)$ is an annualized nxk matrix of related regressors; $\mathbf{B}$ is the nx$4n$ distribution matrix; $\mathbf{X}$ is the $4n$xk matrix of quarterly related regressors; $\mathbf{Bu}$ is the annualized nx1 vector of errors; u is the $4n$x1 vector of quarterly errors; $\mathbf{P}$ is an orthogonal kxk matrix whose columns are the characteristic vectors of $\mathbf{XX}'; \mathbf{BZ} = \mathbf{BXP}$ is the annualized nxk matrix of principal components; $\boldsymbol{\theta}$=$\mathbf{P}'\boldsymbol{\beta}$ is the kx1 vector of coefficients; and $\widehat{\boldsymbol{\theta}} = (\mathbf{BZ}'\mathbf{BZ})^{-1}\mathbf{BZ}'\mathbf{Y}^a$.

Note that the above transformation has not yet provided the dimension-reduction we require since the size of the $\mathbf{Z}$ matrix of orthogonal principle components is the same as the related regressor matrix $\mathbf{X}$. Hence we next briefly describe the procedure and decision criteria by which the number of columns of $\mathbf{Z}$ are reduced to a smaller set which still contain most of the information from the larger set. We start by calculating the correlation matrix $\mathbf{R}$ of the normalized columns of $\mathbf{X}$. The normalization undertaken is to divide the deviation of each variable from its mean by its standard deviations. Thus the total variance of the normalized $\mathbf{X}$ matrix is equal to k or the number of variables. When the dimension of $\mathbf{Z}$ is the same as $\mathbf{X}$ the orthogonal vectors comprising $\mathbf{Z}$ explain all of the variance in normalized $\mathbf{X}$. Accordingly the objective of principle components is to explain as much of the total variance as possible with the least number of principle components or factors. The manner in which the principle factors are calculated, extracting consecutive factors accounts for less and less variance. For example, the fraction of variance explained by each additional factor, FV_i is calculated by first obtaining the characteristic equation of $\mathbf{R}$ which is a polynomial of degree k resulting from expanding the determinant of $|\mathbf{R} - \boldsymbol{\lambda}\mathbf{I}| = 0$ and solving for the eigenvalues λ_i $(i = 1..k)$,where $\sum \lambda_i = tr(\mathbf{R}) = k$. The kx1 vector $\mathbf{FV}$ vector is then calculated as $\mathbf{FV} = \mathbf{T}'\boldsymbol{\lambda}/k$, where $\boldsymbol{\lambda}$ is arranged in the order of the largest to smallest eigenvalue and $\mathbf{T}$ is an upper triangular matrix with zeros below the diagonal and ones on and above the diagonal. The decision rule we employ with respect to how many principle components to retain is that they must explain 99% of the variance of normalized $\mathbf{X}$. This results in our various related regressor sets being reduced to the following number of principle factors: employment=7; hours=7; producer prices=3 and indices of industrial production=4. Finally note that when estimating the elements of $\widehat{\boldsymbol{\theta}}$ both a constant and linear time trend are included in the various $\mathbf{Z}$ matrices.

Data Sources and Definitions

Two-Digit SIC Codes

SIC Code	Industry
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel & Other Finished Products Made from Fabrics
24	Lumber & Wood Products (exc. Furniture)
25	Furniture & Fixtures
26	Paper & Allied Products
27	Printing, Publishing & Allied Industries
28	Chemicals & Allied Products
29	Petroleum Refining & Related Industries
30	Rubber & Miscellaneous Plastics Products
31	Leather & Leather Products
32	Stone, Clay, Glass & Concrete Products
33	Primary Metal Industries
34	Fabricated Metal Products, Except Machinery & Transportation Equipment
35	Industrial & Commercial Machinery & Computer Equipment
36	Electronic & other Electrical Equipment & Components (exc. Computer Equipment)
37	Transportation Equipment
38	Measuring, Analyzing, & Controlling Instruments; Photographic, Medical & Optical Goods; Watches & Clocks
39	Miscellaneous Manufacturing Industries
20-23,26-31	Non-Durable Goods
24-25, 32-39	Durable Goods

NBER Annual Two-Digit Data

N^i	Number of production workers (thous.)
H^i	Number of production worker hours (mill of hours)
y^i	Real total value of shipments ($mill.1987)
m^i	Real total cost of materials ($mill.1987)
$Y^{v,i}$	Nominal total value added ($mill.)
P^i	Deflator for y^i (1987=1)
$P^{m,i}$	Deflator for m^i (1987=1)

BLS Quarterly Two-Digit Data

W^i	Ave hourly earning of production workers

Related Regressors

The 24 BLS employment variables used to distribute N^i include:

1.	Aggregate manufacturing employment
2.	Aggregate production worker employment
3.	Durable industries employment
4.	Durable industries production employment
5.	Non-durable industries employment
6.	Non-durable industries production employment
7-24.	Two digit total employment by industry (except SICs 36 & 38)

The 21 BLS hours variables used to distribute H^i include:

1.	Ave weekly hours of production workers for manufacturing
2.	Ave weekly hours of durable industries production workers
3.	Ave weekly hours of non-durable industries production workers
4-21.	Two digit average weekly hours of production workers (by industry except SICs 36 & 38)

The 23 FRB industrial production indices used to distribute y^i & m^i include:

1.	Total index
2.	Manufacturing
3.	Durable consumer goods
4.	Non-durable consumer goods
5.	Miscellaneous durable goods
6.	Materials
7.	Durable goods materials
8.	Other durable materials
9.	Non-durable goods materials
10.	Energy materials
11.	Automotive products
12.	Foods and tobacco
13.	Clothing
14.	Chemical products
15.	Paper products
16.	Consumer energy products
17.	Business equipment
18.	Transit equipment
19.	Defence and space equipment
20.	Final products and non-industrial supplies
21.	Consumer parts
22.	Equipment parts
23.	Other business supplies ex. energy, motor vehicles & parts., & high-technology

The 43 BLS producer prices used to distribute P^i & $P^{m,i}$ include:

1.	All commodities
2.	Farm products
3.	Processed foods and feeds
4.	Textile products and apparel
5.	Hides, skins, leather, and related products
6.	Fuels and related products and power
7.	Chemicals and allied products
8.	Rubber and plastic products
9.	Lumber and wood products
10.	Pulp, paper, and allied products
11.	Metals and metal products
12.	Machinery and equipment
13.	Furniture and household durables
14.	Non-metallic mineral products
15.	Miscellaneous products
16.	Total durable goods
17.	Total non-durable goods
18.	Manufactured goods
19.	Durable manufactured goods
20.	Non-durable manufactured goods
21.	Total raw or slightly processed goods
22.	Durable raw or slightly processed goods
23.	Non-durable raw or slightly processed goods
24.	Industrial commodities
25.	Farm products, processed foods and feeds
26.	Steel mill products
27.	Finished steel mill products
28.	Crude materials
29.	Crude foodstuffs and feedstuffs
30.	Crude non-food materials except fuel
31.	Crude fuel
32.	Crude materials less agricultural products
33.	Intermediate materials, supplies and components
34.	Food manufacturing
35.	Components for manufacturing
36.	Processed fuels and lubricants
37.	Manufactured animal feeds
38.	Intermediate materials less foods and feeds
39.	Finished goods
40.	Finished consumer goods
41.	Finished consumer foods
42.	Finished consumer foods, processed
43.	Finished consumer goods excluding foods

Appendix 2 - Operationalising the Sectoral NKPC

We next reformulate the Phillips curve described by (28) to obtain a specification more appropriate for estimation. To do so consider the element of marginal cost which is independent of the firm's actions,

$$\widetilde{MC}_t^i = \begin{pmatrix} \frac{W_t^i}{P_t}\left(\alpha_{H,i} + \alpha_{m,i}\left(\frac{W_t^i}{P_t^{m,i}}\frac{\alpha_{m,i}}{\alpha_{N},i}\right)^{\rho_i - 1}\right)^{\frac{-\rho_i}{\rho_i - 1}} \\ +\frac{P_t^{m,i}}{P_t}\left(\alpha_{H,i}\left(\frac{W_t^i}{P_t^{m,i}}\frac{\alpha_{m,i}}{\alpha_H}\right)^{1-\rho_i} + \alpha_{m,i}\right)^{\frac{-\rho_i}{\rho_i - 1}} \end{pmatrix} \psi_i \overline{K}_i^{1-\psi_i}. \tag{45}$$

This can be log-linearised as,

$$\begin{aligned} \widehat{\widetilde{MC}}_t^i &= \frac{\overline{w}^i}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}\right)}(\widehat{W}_t^i - \widehat{P}_t) \\ &\quad + \frac{\frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}\right)}(\widehat{P}_t^{m,i} - \widehat{P}_t) \end{aligned} \tag{46}$$

where $\overline{w}^{i,m} = \frac{\overline{W}^i}{\overline{P}^{m,i}}$ and $\overline{w}^i = \frac{\overline{W}^i}{\overline{P}}$ which allows us to rewrite the Phillips curve as,

$$\begin{aligned} \widehat{\pi}_t^i &= \frac{\beta\alpha_i}{\lambda_i}E_t\widehat{\pi}_{t+1}^i + \frac{\omega_i}{\lambda_i}\widehat{\pi}_{t-1}^i \\ &\quad + \frac{(1-\omega_i)(1-\alpha_i)(1-\alpha_i\beta)}{(1+(\psi_i - 1)\theta_i)\lambda_i}\Bigg(\frac{\overline{w}^i}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}\right)} \\ &\quad (\widehat{W}_t^i - \widehat{P}_t^i) + \frac{\frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{\rho_i}}{\left(\overline{w}^i + \frac{\overline{P}^{m,i}}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H.i}}\right)^{\rho_i}\right)}(\widehat{P}_t^m - \widehat{P}_t^i) + (\psi_i - 1)\widehat{y}_t^i). \end{aligned} \tag{47}$$

Here we can relate the combinations of production function parameters to labor share variables based on gross rather than value-added output. Therefore, since labor share data, and the ratio of intermediate goods to sectoral gross output, $\frac{\overline{P}^m\overline{m}^i}{\overline{p}^i\overline{\widetilde{y}}^i}$ is readily available, we can construct this ratio as, $\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i + \overline{P}^m\overline{m}} = \frac{\overline{\widetilde{s}}^i}{\overline{\widetilde{s}}^i + \frac{\overline{P}^m\overline{m}^i}{\overline{P}^i\overline{\widetilde{y}}^i}} = \frac{\overline{w}^i}{\overline{w}^i + \frac{\overline{P}^m}{\overline{P}}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{n,i}}\right)^{\rho}} = \frac{\alpha_{H,i}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{1-\rho}}{\alpha_{H,i}\left(\overline{w}^{i,m}\frac{\alpha_{m,i}}{\alpha_{H,i}}\right)^{1-\rho} + \alpha_{m,i}}$ and re-write the Phillips curve as,

$$\begin{aligned} \widehat{\pi}_t^i &= \frac{\beta\alpha_i}{\lambda_i}E_t\widehat{\pi}_{t+1}^i + \frac{\omega_i}{\lambda_i}\widehat{\pi}_{t-1}^i + \frac{(1-\omega_i)(1-\alpha_i)(1-\alpha_i\beta)}{(1+(\psi_i - 1)\theta_i)\lambda_i}\Bigg(\frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i + \overline{P}^{m,i}\overline{m}^i} \\ &\quad (\widehat{W}_t^i - \widehat{P}_t^i) + (1 - \frac{\overline{W}^i\overline{H}^i}{\overline{W}^i\overline{H}^i + \overline{P}^{m,i}\overline{m}^i})(\widehat{P}_t^{m,i} - \widehat{P}_t^i) + (\psi - 1)\widehat{y}_t^i). \end{aligned} \tag{48}$$

We can rewrite this in a more conventional form, by defining a gross-output based measure of labor share,

$$\widehat{s}_t^i = \widehat{W}_t^i - \widehat{P}_t^i + \widehat{H}_t^i - \widehat{y}_t^i. \tag{49}$$

Using the log-linearised version of the first-order condition for labor demand this can be re-written as,

$$\begin{aligned}
\widehat{\widetilde{s}}_t^i &= \widehat{W}_t^i + (\psi_i - 1)\widehat{y}_t^i - \frac{\rho_i \alpha_{m,i} \left(\overline{w}^{i,m} \frac{\alpha_{m,i}}{\alpha_{H,i}} \right)^{\rho-1}}{\alpha_{H,i} + \alpha_{m,i} (\overline{w}^{i,m} \frac{\alpha_{m,i}}{\alpha_{H,i}})^{\rho-1}} \widehat{w}_t^{i,m} - \widehat{P}_t^i \\
&= \widehat{W}_t^i + (\psi_i - 1)\widehat{y}_t^i - \rho_i (1 - \frac{\overline{W}^i \overline{H}^i}{\overline{W}^i \overline{H}^i + \overline{P}^{m,i} \overline{m}^i}) \widehat{w}_t^{i,m} - \widehat{P}_t^i.
\end{aligned} \tag{50}$$

This measure of marginal costs can be substituted into our sectoral Phillips curve to give equation (30) in the main text.

Table 4 - Pairwise Tests of Differences Price Contract Duration Across Industries

SIC Code	21	22	23	24	25	26	27	28	30	31	32	33	34	35	37	39
21	0															
22	-3.5	0														
23	-3.4*	0.1	0													
24	1.6***	5.1***	5.0*	0												
25	-3.7*	-0.2	-0.4	-5.4*	0											
26	-0.1	3.4	3.3**	-1.7**	3.7*	0										
27	-2.0	1.6	1.4	-3.6**	1.8	-1.9	0									
28	-2.4**	1.1	1.0	-4.0*	1.4**	-2.3*	-0.4	0								
30	-3.1*	0.4	0.25	-4.8*	0.6	-3.1*	-1.2	-0.8	0							
31	-1.6	1.9	1.8	-3.2*	2.1***	-1.5***	0.4	0.8	1.5	0						
32	-4.5*	-1.0	-1.1	-6.1*	-0.7	-4.4*	-2.5	-2.1*	-1.3***	-2.9**	0					
33	-3.3***	0.3	0.1	-4.9*	0.5	-3.2***	-1.3	-0.9	-0.1	-1.7	1.2	0				
34	-3.7*	-0.2	-0.3	-5.3*	0.0	-3.6*	-1.8	-1.4**	-0.6	-2.1***	0.7	-0.5	0			
35	-6.9*	-3.4	-3.6***	-8.6*	-3.2***	-6.9*	-5.0**	-4.6**	-3.8**	-5.4**	-2.5***	-3.7	-3.2**	0		
37	-10.4**	-6.9	-7.0	-12.0**	-6.6	-10.3**	-8.4	-8.0**	-7.2	-8.8***	-5.9	-7.1	-6.6	-3.4	0	
39	-4.1*	-0.5	-0.7	-5.7*	-0.3	-4.0*	-2.1	-1.7**	-0.9	-2.5	0.4	-0.8	-0.3	2.9**	6.3	0

Statistical sig. is denoted in the following way, ‘*’= 1%, ‘**’ = 5% and ‘***’ = 10%.

Table 5- Pairwise Tests of Differences in ωs across industries

SIC Code	21	22	23	24	25	26	27	28	30	31	32	33	34	35	37	39
21	0															
22	-0.09	0														
23	-0.20**	-0.11***	0													
24	0.15**	0.24*	0.35*	0												
25	-0.28*	-0.19*	-0.08*	-0.43*	0											
26	-0.12*	-0.03	0.08**	-0.27*	0.16*	0										
27	-0.14**	-0.05	0.06	-0.29*	0.14*	-0.02	0									
28	-0.28*	-0.19*	-0.08*	-0.43*	0.00	-0.16*	-0.14*	0								
30	-0.32*	-0.24*	-0.12*	-0.47*	-0.05***	-0.21*	-0.18*	-0.05***	0							
31	-0.03	0.06	0.17*	-0.18*	0.25*	0.09	0.11	0.25*	0.30*	0						
32	-0.17*	-0.08	0.03	-0.32*	0.11*	-0.05	-0.03	0.11*	0.15*	-0.14	0					
33	-0.43**	-0.03	-0.22	-0.57*	-0.14	-0.30**	-0.28***	-0.14	-0.10	-0.40**	-0.25	0				
34	-0.26*	0.16**	-0.05***	-0.40*	0.03	-0.13*	-0.11**	0.03	0.07*	-0.23*	-0.8*	0.17	0			
35	-0.14*	-0.05	0.07	-0.28*	0.14*	-0.15	0.01	0.14*	0.19*	-0.11	0.04	0.29***	0.11*	0		
37	-0.02	0.07	0.18*	-0.17**	0.26*	-0.10**	0.12**	0.26*	0.31*	0.01	0.15*	0.41**	0.24*	0.12**	0	
39	-0.29*	-0.20*	-0.08**	-0.43*	0.0	-0.16*	-0.14**	0.00	0.04	0.26*	-0.11**	0.14	-0.03	-0.15*	-0.27*	0

Statistical sig. is denoted in the following way, ‘*’= 1%, ‘**’ = 5% and ‘***’ = 10%.