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

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Abstract

In this paper we estimate New Keynesian Phillips Curves (NKPC) for US manufacturing industries defined at the SIC 2-digit level over the period 1959 to 1996. This enables us to measure the extent of nominal inertia across industrial sectors. A key innovation in this research is the use of intermediate goods costs rather than labor costs as a measure of marginal costs. Intermediate goods costs are a more significant element of costs for the firms populating our sample and are not subject to the criticism that wage rates are non-allocative. We find that there is statistically significant variability in estimates of price stickiness, ranging from 8 months to 2.5 years. We also find that estimates of backward-looking price-setting behavior vary, with some industries characterized by 80% of pricing decisions made in a purely forward-looking manner, while in others only 50% of pricing decisions are made that way. Market power (as captured by the Herfindahl-Hirschman index) appears to be associated with increased price stickiness, but reduced rule-of-thumb behavior in setting prices. Finally, firms are also more likely to follow simple rules of thumb when output in their industry is more volatile.

JEL Codes:E3

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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 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 (2002), 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 (2005)) 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-linearized 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 and propose an alternative measure of marginal costs based on intermediate goods costs rather than labor costs, which we argue is likely to be a better proxy for marginal costs for the industries in our sample[1]. 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 (2002) sectoral differences stem from demand-side variations between 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

[1] Indeed, we find that replicating the regressions of this paper using labor share data as a measure of marginal costs yields implausible measures of the degree of price stickiness. These results are available upon request.

'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, Barsky *et al.* (2005) 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. 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 construct sector specific versions of the hybrid New Keynesian Phillips curve along the lines of Gali *et al.* (2001) or Leith and Malley (2005), where firms can change their prices after random intervals of time as in Calvo (1983). However, rather than focus on labor's share as a measure of marginal cost, as is common in aggregate studies, we derive a measure of marginal cost largely driven by the ratio of the value of intermediate goods used in production to gross output. We do this for several reasons. Firstly, intermediate goods are a significant part of firm costs within US manufacturing (see Table 1 below). Secondly, within our dataset, there are only data for the wage costs associated with production workers, and this may be too narrow a definition of labor input to accurately capture marginal costs through the conventional labor share measure. Thirdly, some authors question whether the measured hourly wage rate really plays an allocative role and as such labor cost based measures of marginal cost may be inappropriate (see, for example, Blinder *et al* (1998), Chapter 1). Finally, intermediate goods are not subject to concerns about varying effort levels or utilization rates in the same way as labor and capital inputs.

The importance of material costs within US manufacturing industries is highlighted in Table 1 below which details the average ratio of production worker wage costs, W^iH^i, to gross output, P^iy^i and the ratio of material costs, $P^{m,i}m^i$, to gross output. From the first two columns in Table 1 it is clear that material/intermediate goods costs are a far more significant part of variable costs than production worker labor costs for all the 2-digit manufacturing industries considered in the table.

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. The average duration of price contracts is 15.7 months and durable goods industries are relatively more sticky than non-durable goods industries. Our econometric work also suggests that around two thirds of firms set prices optimally, in a forward-looking manner, rather than following backward-looking rules of thumb. Additionally, market power (as captured by the Herfindahl-Hirschman index) tends to be associated with stickier prices, but less backward-looking behavior. 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.

Table 1 - Costs in US Manufacturing Industries

SIC	Industry	$\frac{W^i H^i}{P^i y^i}$	$\frac{P^{m,i} m^i}{P^i y^i}$
	Aggregate Manufacturing	0.115	0.682
20	Food and Kindred Products	0.063	0.673
21	Tobacco Products	0.071	0.717
22	Textile Mill Products	0.155	0.598
23	Apparel & Other Finished Products	0.185	0.519
24	Lumber & Wood Products (exc. Furniture)	0.168	0.590
25	Furniture & Fixtures	0.187	0.482
26	Paper & Allied Products	0.121	0.557
27	Printing, Publishing & Allied Industries	0.154	0.350
28	Chemicals & Allied Products	0.064	0.485
29	Petroleum Refining & Related Industries	0.025	0.831
30	Rubber & Miscellaneous Plastics Products	0.152	0.493
31	Leather & Leather Products	0.180	0.512
32	Stone, Clay, Glass & Concrete Products	0.163	0.450
33	Primary Metal Industries	0.128	0.617
34	Fabricated Metal Products	0.165	0.499
35	Industrial and Commercial Machinery & Computer Equipment	0.145	0.462
37	Transportation Equipment	0.114	0.595
39	Miscellaneous Manufacturing Industries	0.154	0.465

The data used in this table are described in Appendix 1. Note that lack of data for the full sample prevent the use of industries 36 and 38

The rest of the paper is organized as follows. In Section 2 we derive our sectoral *NKPCs* in the presence of intermediate/material good inputs. In Section 3 we describe our data and estimate the model for 18 2-digit US manufacturing industries. Section 4 contains our conclusions.

2 The Model

The New Keynesian Phillips Curve (*NKPC*) derived under the assumption that firms can only change prices at random intervals of time (as set out in Woodford (2003), Chapter 3, for example) implies that current inflation is related to expectations of future inflation as well as the current value of marginal costs. In applying this description of inflation dynamics to industrial sectors, we follow Gali and Gertler (1999) in allowing some firms to set prices according to a backward-looking rule-of-thumb. Specifically inflation in each industry, i, obeys,

$$\widehat{\pi}_t^i = \frac{\beta\alpha_i}{\lambda_i}E_t\widehat{\pi}_{t+1}^i + \frac{\omega_i}{\lambda_i}\widehat{\pi}_{t-1}^i + \frac{(1-\omega_i)(1-\alpha_i)(1-\alpha_i\beta)}{\lambda_i}(\widehat{MC}_t^i) \tag{1}$$

where $\lambda_i = \omega_i + \beta\omega_i\alpha_i + \alpha_i - \omega_i\alpha_i$. The parameter $1-\alpha_i$ is the probability of price change in a given period in industry i, ω_i are the proportion of firms that follow a backward-looking rule of thumb which indexes their price to last-period's average (sectoral) reset price plus observed inflation and β is firms' steady-state discount factor. The variable $\widehat{\pi}_t^i$ is the (demeaned) rate of output price inflation in sector i and $\widehat{MC}_t^i$ is a log-linearized measure of marginal costs derived below.

2.1 Defining Marginal Cost

We now turn to consider the form of the firm's production function in order to define marginal cost within each sector. We adopt a *CES* form for production where firms combine intermediate goods m_t^i along side another factor $f_{t.}^i$ This second factor of production can be thought of as an aggregate of all other factors of production e.g. labor and capital, which can be disaggregated and modelled as desired. Our representative firm's production function is therefore given by,

$$y_t^i = \left(\lambda_{f,i}(f_t^i)^{1-\rho_i} + \lambda_{m,i}(m_t^i)^{1-\rho_i}\right)^{\frac{1}{1-\rho_i}} \tag{2}$$

where $\lambda_{f,i}$ and $\lambda_{m,i}$ are distribution parameters within the CES production function, and $1/\rho_i$ is the elasticity of substitution between intermediates and our second composite factor. The marginal product of materials is,

$$\frac{\partial y_t^i}{\partial m_t^i} = \lambda_{m,i}\left(\frac{y_t^i}{m_t^i}\right)^{\rho_i}. \tag{3}$$

Defining the costs share of intermediates as,

$$s_t^{m,i} = \frac{P_t^{m,i}m_t^i}{P_t^i y_t^i} \tag{4}$$

where $P_t^{m,i}$ is the price of intermediate goods and P_t^i the price index associated with output in sector i, we can write real marginal cost for sector i as,

$$MC_t^i \equiv \frac{P_t^{m,i}}{P_t^i}\frac{\partial m_t^i}{\partial y_t^i} = \frac{1}{\lambda_{m,i}}\left(s_t^{m,i}\right)^{\rho_i}\left(p_t^{m,i}\right)^{1-\rho_i} \tag{5}$$

where $p_t^{m,i} = \left(\frac{P_t^{m,i}}{P_t^i}\right)$ is the relative price of materials. Therefore, log-linearized marginal costs can be written as,

$$\widehat{MC}_t^i = \rho_i \widehat{s}_t^{m,i} + (1-\rho_i)\widehat{p}_t^{m,i}. \tag{6}$$

and substituted into our *NKPC* above.

3 Estimation and Empirical Results

We next briefly discuss some issues pertaining to the data and the econometric estimator prior to presenting our results and analysis.

3.1 Measurement Issues

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 as low as 4 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 the use of annual data since $1/(1-\alpha_i)$, the average number of months that prices remained fixed, would be constrained to be no less than one year.

Given these considerations, 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; real intermediate inputs, m^i and the implicit price deflator for intermediate inputs, $P^{m,i}$. Unfortunately, higher frequency industry level data (i.e. quarterly or monthly) for intermediate inputs and their corresponding prices is not available. While the Bureau of Labor Statistics (BLS) reports prices on a sub-aggregate manufacturing basis there are several problems with these measures in the context of our research. 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[2].

In contrast, the data provided in the National Bureau of Economic Research (NBER) annual Productivity Database has the major advantage that its measures provide an very good match with the requirements of the theory, but the data is annual. Therefore, to estimate the unobserved quarterly movements in the annual NBER data we employ the distribution method developed by Fernandez (1981). The Fernandez approach generalizes the model set out Chow and Lin (1971) and relies on estimating the relationship between the annual NBER data and the related quarterly series obtained from the BLS and FRB. While 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. Full details of the our application of the approach are given in the Appendix. Finally note that all of the quarterly 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.

3.2 Estimator

Using the data described above, 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). This implies the estimation of 54 parameters (i.e. 3x18 'deep' parameters) [3]. These parameters include the probability that a firm in sector i cannot 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 determining the elasticity of substitution between intermediate goods and other factors, 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.

[2] 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.

[3] Although the theory allows us to estimate the steady-state discount factor, β, we find that this is implausibly low if estimated freely. This is a common problem in estimating models of this type (see for example, Ireland (2004)). Therefore we choose, following Rotemberg and Woodford (1998) to calibrate the discount factor as $\beta = 0.99$ which is consistent with an annualised risk-free real interest rate of 3%.

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 system of orthogonality conditions suggested by the RE hypothesis applied to each sectoral Phillips curve[4]. The instruments we employ are specific to each industry and include a constant term, one period lags of industry-specific inflation, the share of intermediate goods in output and the real price of intermediate goods. In line with our theory the instruments are all demeaned. To obtain standard errors which are robust to heteroscedasticity and autocorrelation of unknown form, we calculate the covariance matrix of sample moments using the Newey and West (1987) estimator[5]. 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.

3.3 Interpretation of Results

The results of estimating the system of 18 2-digit industries are detailed in Table 2. The first three columns give parameter estimates with the associated standard error in brackets. The fourth column calculates the average length of time in months it takes to adjust all prices in a given industry, $\left(\frac{1}{1-\alpha_i}\right) \times 3$ based on our estimates of the probability of not being able to change prices in a given quarter, $\alpha_{i.}$ The final column measures the adjusted R^2 for each equation. Descriptions of the industries corresponding to the SIC codes can be found in Table 1 in the Introduction. There are several things to note about these results. Firstly, with the exception of industry 24 (Lumber & Wood Products (exc. Furniture)) all estimates of the degree of price-stickiness are statistically significant and plausible. Of the remaining industries, the most flexible industry is 29 (Petroleum Refining and Related Industries) and the least flexible, 33 (Primary Metal Industries). In all industries, other than 24, there is also a significant degree of backward-looking behavior, although around two thirds of prices are set in a profit-maximizing manner.

[4] Although several recent papers question the robustness of GMM in this context (see Rudd and Whelan (2005) and Lindé (2005)), Galí *et al.*, (2005) convincingly refute these claims.

[5] In the estimations reported in Table 2, the lag truncation parameter 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 robust to alternative values of the lag truncation parameter, 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.

Table 2 - Estimation Results

Sic Code	α_i	ω_i	ρ_i	$\left(\frac{1}{1-\alpha_i}\right) \times 3$	$\overline{R}^2$
20	0.820 [0.000]	0.250 [0.016]	0.416 [0.259]*	16.6	0.31
21	0.866 [0.000]	0.249 [0.046]	0.893 [0.595]*	22.3	0.37
22	0.751 [0.000]	0.399 [0.027]	1.080 [0.000]	12.1	0.57
23	0.799 [0.000]	0.484 [0.000]	0.723 [0.025]	14.9	0.79
24	1.011 [0.771]*	0.375 [0.776]*	5999.3 [1.000]*	NA	0.47
25	0.805 [0.000]	0.466 [0.003]	0.950 [0.000]	15.4	0.84
26	0.889 [0.000]	0.445 [0.011]	1.373 [0.360]*	27.1	0.49
27	0.808 [0.000]	0.280 [0.000]	0.994 [0.000]	15.6	0.63
28	0.768 [0.000]	0.442 [0.001]	1.152 [0.000]	12.9	0.82
29	0.634 [0.000]	0.196 [0.016]	1.029 [0.000]	8.2	0.19
30	0.747 [0.000]	0.473 [0.003]	1.039 [0.000]	11.9	0.83
31	0.720 [0.000]	0.427 [0.000]	1.181 [0.000]	10.7	0.56
32	0.804 [0.000]	0.240 [0.016]	1.180 [0.000]	15.3	0.72
33	0.901 [0.000]	0.522 [0.001]	4.622 [0.819]*	30.2	0.63
34	0.692 [0.000]	0.316 [0.002]	1.042 [0.000]	9.7	0.78
35	0.856 [0.000]	0.288 [0.007]	2.140 [0.139]*	20.8	0.63
37	0.890 [0.000]	0.240 [0.053]	0.726 [0.300]*	27.4	0.58
39	0.751 [0.000]	0.421 [0.000]	1.059 [0.000]	12.0	0.81

Notes: (1) $p-values$ are in square brackets; (2) a star indicates not significant at the 5% level; (3) NA is not applicable; (4) $N = 153$, J-stat with 18 df is 17.6 with a $p-value$ of 0.483; (5) column 5 is measured in months.

With the exception of industry 24 - Lumber & Wood Products (exc. Furniture), which has an implausibly large (but insignificant) estimated ρ_i, implying a near Leontief production function, the estimates of ρ_i are also plausible and often do not differ much from the Cobb-Douglas case of $\rho_i = 1$. However for some industries (20, 21, 24, 26, 33, 35 and 37 at the 5% level) this elasticity is not well determined in the sense that it is not statistically significant. Further note that application of a series of unit root tests (e.g. Dickey-Fuller, Weighted Symmetric 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. 1 to 12)[6].

We next assess the extent to which these results are statistically significantly different across industries. To do so, we first test for equality of each parameter across industries in our sample (as well as for durable goods industries (SIC 24, 25, 32-39) and non-durable goods (SIC 20-23, 26-31) industries). This suggests that there are significant differences in estimates of price-stickiness, α_i, and the extent of rule-of-thumb behavior, ω_i, across industries which is also present when looking at durable/non-durable subgroups of industries. These asymmetries across industries are likely to be of concern to monetary policy makers for the reasons discussed in the Introduction. The ρ_i parameters (which define the elasticity of substitution between intermediate goods and other factors of production, $1/\rho_i$) are only found to be statistically significantly different within the durable goods industries.

Table 3 - Parameter Differences

Sic Code	$\chi^2(1)$	$p-val$
Equality of α_i's	622.74	[0.000]
Equality of ω_i's	45.68	[0.000]
Equality of ρ_i's	0.894	[0.344]
Equality of durable α_i's	275.57	[0.000]
Equality of durable ω_i's	28.62	[0.000]
Equality of durable ρ_i's	0.227	[0.634]
Equality of non-durable α_i's	371.27	[0.000]
Equality of non-durable ω_i's	35.10	[0.000]
Equality of non-durable ρ_i's	13.490	[0.000]

Notes:(1) durables=24-25, 32-39; non-durable=20-23, 26-31;
(2) industry 24 has been excluded from these calculations;
(3) the null of equality for the ρ_i's & the durable ρ_i's can be rejected if the insignificant ρ_i's from Table 1 are excluded.

[6] These results are not reported here to preserve space but will be made available on request.

We next compare results in aggregate by constructing a weighted-average of parameter estimates across industries in Table 4. The weighted average estimate of α of 0.81 implies that prices remain fixed for, on average, 15.7 months in US manufacturing, with just under one third of pricing decisions following a backward-looking rule-of-thumb. Blinder *et al.* (1998) finds, in a survey of 430 firms, that the median frequency of price change is around one year[7]. Our weighted average estimate of an average probability of price stickiness across all manufacturing industries implies an average duration of 15.7 months which is slightly higher than this survey evidence, although not statistically significantly so. The next two columns calculate the averages for the durable goods industries and non-durable goods industries, respectively. The final column assesses the extent to which these weighted averages differ across the durable and non-durable industry subgroups [8].

Table 4 -Weighted Coefficient Estimates and Standard Errors

	Aggregate (1)	Durables (2)	Non-Durables (3)	(2)-(3)
α	0.810	0.841	0.782	0.059
	(0.026)	(0.022)	(0.016)	(0.027)
ω	0.332	0.324	0.339	-0.015
	(0.041)	(0.024)	(0.029)	(0.038)*
ρ	1.323	1.801	0.884	0.917
	(1.660)*	(1.629)*	(0.098)	(1.631)*
months	15.9	18.9	13.8	5.1

Notes (1) industry 24 has been excluded from these calculations; (2) the standard errors (in brackets) allow for non-zero covariances in the weighted covariance matrix; (3) a star indicates not significant at the 5% level.

We construct Table 4 to explore the extent of systematic differences in price-setting behavior between the durable/non-durable goods industry subgroups, since various structural differences between these groups were emphasized as being important for monetary policy in the studies cited in the Introduction. We find that the average degree of price stickiness in durable and non-durable goods industries is statistically significantly different, with

[7] It should be noted that Bils and Klenow (2002) estimate the frequency of price changes to be higher. However, as noted by the authors themselves, their sample differs from other surveys by focusing on final consumer goods. The Blinder *et al.* (1998) survey, for example, focuses on the pricing behaviour of firms more likely to be producing intermediate goods. These are similar to the kinds of firms populating our data.

[8] Here we exclude the implausible results for industry 24.

durable goods industries featuring more nominal inertia than non-durable goods industries. However, for other parameters there are no significant differences in the weighted average parameters across the two groups[9].

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 Table 5 which computes correlation coefficients between the sectoral parameter estimates, the Herfindahl-Hirschman index of industry concentration[10] and the extent of output and inflation variability[11]. Here several interesting patterns emerge. Firstly, there is no clear correlation between the degree of price-stickiness and the extent of backward-looking behavior. However, market-power, as measured by the Herfindahl-Hirschman index, is clearly positively correlated with the estimated measure of price-stickiness, and negatively related to the estimated proportion of rule-of-thumb price-setting firms. In other words, the less competitive an industry the more sticky its price-setting behavior and the more likely it is to set prices in a forward-looking manner. This positive correlation between price stickiness and industry concentration is also found in the study by Bils and Klenow (2002). However, it is difficult to map between our two modes of price-setting and the firm-level questionnaire of Blinder *et al.* (1998). They find (see page 307) that firms often delay price increases until after costs have risen, even when they can predict future cost increases, but that when they do change prices they do so in one go. While our profit-maximizing price-setters should anticipate future cost increases, the time dependent nature of the Calvo rule may imply that costs have changed before they are able to adjust prices. Our modelled pricing behavior is also consistent with the absence of gradual adjustment in individual prices. As might be expected, there is a positive correlation between output variability and the extent of price stickiness, and a negative relationship between infla-

[9] It should be noted, as shown in Table 3, that this is consistent with significant differences in parameter estimates between individual industries.

[10] The data for the industry concentration ratios and the HH indices were obtained from the 2001 U.S. Census Bureau publication Concentration Ratios in Manufacturing EC97M31S-CR, Table 2. The data reported in this publication are based on the 1997 NAICS system. Compared to the 1987 2-digit SIC system which we employ in our estimations, the major changes include: (i) the creation of a new computer and electronic product manufacturing sector; (ii) publishing and logging were moved to other sectors; and (iii) bakeries and custom manufacturing moved were into manufacturing. Aside from these there is a reasonable degree of correspondence between the two systems at the major product level. Note that (i) above does not create any difficulties for our comparisons since SIC 36 and SIC 38 have been excluded from our estimations due to data unavailability.

[11] Output variability is measured as the average squared deviation of gross output from a logarithmic trend. Inflation variability is the same measure for demeaned inflation.

tion variability and price stickiness. Finally, it appears that greater volatility in output is associated with firms adopting backward-looking rules of thumb in price-setting, possibly reflecting the difficulties in forecasting demand in such an environment.

Table 5 - Patterns in the Estimates - All Industries

	α^i	ω^i	ρ^i	Var(y^i)	Var(π^i)	HH_i
α^i	1					
ω^i	0.094	1				
ρ^i	0.369	0.382	1			
Var(y^i)	0.111	0.193	0.788	1		
Var(π^i)	-0.509	-0.358	0.016	0.067	1	
HH_i	0.308	-0.458	-0.177	-0.084	0.169	1

4 Conclusions

In this paper we estimated a sectoral version of the New Keynesian Phillips Curve based on Calvo (1983) contracts, which yielded measures of the degree of price stickiness in each industry. Our specification also discriminated 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. A key innovation in our approach was basing our measure of marginal costs on the costs of intermediate goods, which we argue are likely to be a better proxy for marginal costs than labor cost data for the industries in our sample. In the econometric estimation we also obtained a measure of the elasticity of substitution between this and other factors in production.

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 8 months to 2.5 years, with an average duration of 15.7 months. There was statistically significant variation between individual industries, which implies that the sectoral response to monetary policy is likely to be quite different. We also found that the majority of firms' set prices in a forward-looking manner consistent with profit-maximization, although, almost all industries also had a significant degree of backward-looking behavior (typically one third of prices were set in a backward-looking way) in price-setting, especially when output in that industry was more volatile. Finally, sectors with greater industrial concentration were found to face more inertia in price setting, but to be less likely to change prices in a backward-looking manner.

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)). Evolving industrial composition and sectoral differences are also likely to affect the monetary policy transmission mechanism over time. 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

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 Chow 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.

$$y_t^a = \frac{(y_{t,1} + y_{t,2} + y_{t,3} + y_{t,4})}{4}. \tag{7}$$

When estimating the quarterly values it is assumed 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:

$$y_{t,i} = x_{t,i}^1\beta_1 + x_{t,i}^2\beta_2 + ... + x_{t,i}^k\beta_k + u_{t,i} \tag{8}$$

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 $(\mathbf{D'D})^{-1}$, where the $4n$x$4n$ $\mathbf{D}$ matrix is given by

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & 0 & . & . & . & . & 0 & 0 \\ -1 & 1 & 0 & 0 & . & . & . & . & 0 & 0 \\ 0 & -1 & 1 & 0 & . & . & . & . & 0 & 0 \\ . & . & . & . & & & & & . & . \\ . & . & . & . & & & & & . & . \\ 0 & 0 & 0 & 0 & . & . & . & . & -1 & 1 \end{bmatrix}. \tag{9}$$

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 (8) we require a nx$4n$ distribution matrix $\mathbf{B}$, .e.g

$$\mathbf{B} = (1/4)\begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & . & . & . & . & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & & & & & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & & & & . & . & . & . \\ . & . & . & . & . & . & . & . & & & & & . & . & . & . \\ . & . & . & . & . & . & . & . & & & & & . & . & . & . \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & . & . & . & . & 1 & 1 & 1 & 1 \end{bmatrix}. \tag{10}$$

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 (10) it follows that,

$$\mathbf{Y}^a = \mathbf{BY} = \mathbf{BX}\boldsymbol{\beta} + \mathbf{Bu} = \mathbf{X}^a\boldsymbol{\beta} + \mathbf{u}^a. \tag{11}$$

Based on the Chow and Lin (1971) analysis it can be easily shown that the optimal linear unbiased estimator for the unobserved higher frequency movements in $\mathbf{Y}$ is given by

$$\widehat{\mathbf{Y}} = \mathbf{X}\widehat{\boldsymbol{\beta}} + (\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}'(\mathbf{B}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}')^{-1}\widehat{U}^a \tag{12}$$

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 (12) pertains to the choice of the appropriate k quarterly related regressors which make up the columns of **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 cases 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. 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 (11) above can be transformed as follows

$$\mathbf{Y}^a = \mathbf{BX}\boldsymbol{\beta} + \mathbf{Bu} = (\mathbf{BXP})(\mathbf{P}'\boldsymbol{\beta}) + \mathbf{Bu} = \mathbf{BZ}\boldsymbol{\theta} + \mathbf{Bu} \tag{13}$$

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[12]

Two-Digit SIC Codes and Definitions are given in Table 1.

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

[12]Further detail on the related regressors is available on request.