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by

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DISCUSSION
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Inflation Dynamics and Real Marginal Costs: New Evidence from U.S. Manufacturing Industries*

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Abstract

This paper deals with the analysis of price-setting in U.S. manufacturing industries. Recent studies have heavily criticized the ability of the New Keynesian Phillips curve (NKPC) to fit aggregate inflation [see, e.g., *Rudd and Whelan, 2006, Can Rational Expectations Sticky-Price Models Explain Inflation Dynamics?, American Economic Review, vol. 96(1), pp. 303-320*]. We challenge this evidence, showing that forward-looking behavior as implied by the New Keynesian model of price-setting is widely supported at the sectoral level. In fact, current and expected future values of the income share of intermediate goods emerge as an effective driver of inflation dynamics. Unlike alternative proxies for the forcing variable, the cost of intermediate goods presents dynamic properties in line with the predictions of the New Keynesian theory.

JEL: E31, L60

Keywords: New Keynesian Phillips Curve; Aggregation; Sectoral Data; Intermediate Goods

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1 Introduction

In the last decade the New Keynesian Phillips curve (NKPC hereafter) has become an important workhorse in the study of inflation dynamics. In light of the key role played by this relationship in modern monetary policy analysis, a vast literature has developed with the aim of testing its validity on empirical grounds. To this end, most of the existing contributions have relied on aggregate data. Among others, Galí and Gertler (1999), Woodford (2001) and Sbordone (2002) report evidence in support of the NKPC. More recently, their findings have been extensively criticized in a series of papers by Jeremy Rudd and Karl Whelan,[1] who show that the type of rational forward-looking behavior embodied in the NKPC finds poor empirical support. The present paper contributes to this debate, showing that aggregation plays a central role in the analysis of Rudd and Whelan.

We explore inflation dynamics in U.S. manufacturing industries defined at the SIC four digit level. Looking at sectoral inflation is important in that it allows us to account for the role of heterogeneous price-setting[2] in producing biased estimates of the "aggregate" NKPC. As in Rudd and Whelan (2006), we focus on the testable implications of the closed-form solutions to both purely forward-looking and hybrid versions of the NKPC. Our evidence suggests that imposing sectoral homogeneity may result in overstating the relative importance of lagged inflation, while under-estimating the impact of current and future expected realizations of the driving term. This result bears close resemblance with that of Imbs et al. (2007), who are primarily focused on the direction and magnitude of the bias in aggregate estimates.[3] We complement their study, showing that aggregation plays a central role also in the empirical validation of forward-looking behavior as implied by the NKPC. Employing an appropriate proxy for the driving term of inflation dynamics is paramount to our results, as the selected variable needs to display dynamic properties in line with the predictions of the New Keynesian theory (see Galí and Gertler, 1999). We consider both cost-based measures and detrended output at the sectoral level. Among these variables, only the income share of intermediate goods implies a counter-cyclical mark-up, while co-moving negatively (positively) with past (future) inflation,

[1] See Rudd and Whelan (2005a, 2005b and 2006). Rudd and Whelan (2007) survey the main results in this strand of the literature.

[2] A number of papers exploring sectoral price-setting indicate that the degree of price rigidity can change markedly across sectors (see, e.g., Bils and Klenow, 2004, Dhyne et al., 2006, Nakamura and Steinsson, 2008).

[3] Imbs et al. (2007) base their study on the initial premise that both the forward and backward looking terms in the NKPC are relevant for inflation dynamics, as earlier established by Galí and Gertler (1999). As such, their analysis may be subject to the criticism expressed by Rudd and Whelan (2005b).

as postulated by Rotemberg and Woodford (1991).

We document widespread sectoral evidence in support of the price-setting mechanism embodied in the NKPC. Specifically, a hybrid NKPC featuring preponderance of forward-looking price setters can closely predict inflation dynamics in a large number of sectors, although most of inflation variability is accounted for by its lagged term. Most importantly, the slope of the NKPC is on average significant for the manufacturing industry as a whole, with the sectoral estimates indicating that current and expected future values of the income share of input materials exert a statistically significant (and economically meaningful) impact on the rate of inflation in a large number of sectors.[4] We also show that our implied estimates of price rigidity are in substantial agreement with those obtained by Nakamura and Steinsson (2008) from highly disaggregated U.S. data on producer price indices. This evidence reinforces our confidence in the NKPC as a plausible model of price-setting: although the estimated impact of the forcing variable may generally appear rather low, yet it reflects empirically relevant frequencies of price changes.

The remainder of the paper is laid out as follows: Section 2 sketches a simple model for the analysis of sectoral inflation dynamics; Section 3 presents the dataset and some preliminary results on the fit of alternative dynamic specifications of the NKPC; Section 4 presents evidence from the GMM estimation of the NKPC and examines the role of heterogeneity in producing biased estimates at the aggregate level; Section 5 includes additional evidence in support of the results presented in the previous section; Section 6 concludes.

2 Sectoral Inflation Dynamics

Consider an economy with I sectors of production, each sector being composed of a continuum of firms producing differentiated products. The production of each good is carried out by combining intermediate goods and labor. Specifically, the zth firm in the ith sector employs a Cobb-Douglas production technology with constant returns to scale:

$$Y_{it}(z) = M_{it}(z)^{1-\alpha_i} L_{it}(z)^{\alpha_i}, \tag{1}$$

[4] Alternatively, using other proxies, such as detrended output and the labor income share, returns poor evidence.

where $Y_{it}(z)$, $L_{it}(z)$ and $M_{it}(z)$ denote the gross product, labor and material inputs employed by firm z in sector i, respectively. At any given period, each firm minimizes its cost of production to meet demand at the equilibrium price. The first order conditions from this problem result into the following relationships:

$$MC_{it}(z)\,Y_{it}(z) = \frac{W_{it}L_{it}(z)}{\alpha_i} = \frac{P_{it}^{M}M_{it}(z)}{1-\alpha_i}, \tag{2}$$

where $MC_{it}(z)$ is the nominal marginal cost faced by firm z in sector i, while W_{it} and P_{it}^{M} denote the nominal wage and the price of the bundle of input materials in the ith sector. Under the assumption of within-sector homogeneity, (2) implies that the sector-specific real marginal cost (RMC_{it}) is proportional to the labor share of income ($S_{it}^{L} \equiv (W_{it}L_{it})(P_{it}Y_{it})^{-1}$) and the income share of intermediate goods ($S_{it}^{M} \equiv \left(P_{it}^{M}M_{it}\right)(P_{it}Y_{it})^{-1}$).

Assuming that firms are able to reset their prices at random intervals of time (Calvo, 1983) implies that the rate of inflation can be expressed as a function of expected inflation and the real marginal cost. Linearizing and aggregating the pricing decisions of firms in each sector produces the following sector-specific NKPC:

$$\pi_{it} = \beta E_t \pi_{it+1} + \gamma_i\left(rmc_{it} + \phi_i\right) + \eta_{it}, \qquad \forall i, \tag{3}$$

where π_{it} denotes sector-specific inflation, rmc_{it} is the logarithm of the real marginal cost in the ith sector, η_{it} is an *iid* exogenous cost-shifter, β denotes the steady-state discount factor, $\phi_i = \log(\epsilon_i/(\epsilon_i - 1))$ is the steady-state sector-specific mark-up (where ϵ_i denotes the elasticity of substitution between goods produced in the ith sector) and $\gamma_i = (1-\beta\theta_i)(1-\theta_i)\,\theta_i^{-1}$, where $1-\theta_i$ is the probability faced by sector i producers of being able to reset prices in a given period.

A key implication of the NKPC is that inflation depends on current and expected future realizations of the forcing variable:

$$\pi_{it} = \gamma_i E_t \sum_{s=0}^{\infty} \beta^s x_{it+s} + \eta_{it}, \tag{4}$$

where x_{it} is meant to capture variability in the real marginal cost. When taking the NKPC to the data, a first problem relates to the choice of an appropriate proxy for x_{it}. The evidence on this topic is widespread. Among others, Galí and Gertler (1999) emphasize the importance of using direct measures of the real marginal cost, such as the labor share of income.[5] Alternatively, Leith and Malley (2007) use a proxy based on the cost of intermediate goods.[6] It should be noted that using the income shares of the sectoral production factors entails some advantages, compared to employing their aggregate counterparts. First, as noted by Nekarda and Ramey (2009) and Lawless and Whelan (2011), focusing on industrial rather than aggregate data helps to overcome problems related with sectoral shifts, which are likely to bias the analysis of aggregate inflation dynamics. Most importantly, working with sectoral data allows us to use explicit measures of gross output to build a proxy for the real marginal cost. Otherwise, at the economy-wide level we could only exploit statistics on valued added, which cannot be regarded as a valid output measure in a monopolistically competitive setting (Basu and Fernald, 1997).

In alternative, various contributions (e.g., Furher and Moore, 1995) advocate the use of output gap measures as indicators of real economic activity. To enhance comparability with previous studies, we also proxy x_{it} with a measure of (sectoral) detrended output. Although a log-linear relationship can usually be established between the real marginal cost and the output gap in otherwise standard New Keynesian models, the presence of input materials implies a wedge between gross output and consumption (or value added), as part of the goods produced in each sector are also used as inputs of production (see, e.g., Nakamura and Steinsson, 2010). Thus, measures of detrended output do not account for the existence of the intermediate input channel and its role in the propagation of shocks to the system (Petrella and Santoro, 2011).

2.1 The Persistence Problem: a Hybrid Specification

A relevant implication of model (3) is that it does not account for the key role played by lagged dependent variables in inflation regressions (see, e.g., Fuhrer, 2006). To overcome this, a number of mechanisms have been proposed to incorporate frictions into optimizing rational expectations models, so as to rationalize the introduction of lagged inflation in the NKPC. Assuming that a fixed proportion of firms reset their price following an indexation rule allows us to obtain a "hybrid" NKPC:

$$\pi_{it} = \varphi_i E_t \pi_{it+1} + (1 - \varphi_i)\, \pi_{it-1} + \gamma_i \left(rmc_{it} + \phi_i \right) + \eta_{it},\ 0 \leq \varphi_i \leq 1, \tag{5}$$

[5] See also Sbordone (2002, 2005) and Galí et al. (2005).

[6] In fact, intermediate goods correspond to the largest determinant of the total cost of production. Dale Jorgenson's data on input expenditures by US industries show that input materials (including energy) account for roughly 50% of outlays, while labor and capital only account for 34% and 16% respectively.

where, as in Rudd and Whelan (2006), we assume that current inflation depends on a convex combination of its expected future value and its lag,[7] implying that $\beta = 1$ and $\gamma_i = (1-\theta_i)^2 \theta_i^{-1}$. Within the class of papers employing variants of this hybrid specification some of the most prominent examples – such as Fuhrer and Moore (1995) and Christiano et al. (2005) – have set $\varphi \leq 1/2$. However, there is no compelling evidence to argue a priori in favor of price-setting behavior with preponderance of backward-looking price-setters. Equation (5) allows for two solutions that depend on φ_i:

$$\Delta\pi_{it} = \frac{\gamma_i}{1-\varphi_i} E_t \sum_{s=0}^{\infty} \left(\frac{\varphi_i}{1-\varphi_i}\right)^s (rmc_{it+s} + \phi_i) + \frac{1}{1-\varphi_i}\eta_{it}, \quad \text{for} \quad \varphi_i \leq 1/2, \tag{6}$$

$$\pi_{it} = \frac{1-\varphi_i}{\varphi_i}\pi_{it-1} + \frac{\gamma_i}{\varphi_i} E_t \sum_{s=0}^{\infty} (rmc_{it+s} + \phi_i) + \frac{1}{\varphi_i}\eta_{it}, \quad \text{for} \quad \varphi_i > 1/2. \tag{7}$$

Rudd and Whelan (2006) report evidence suggesting that the hybrid model describes aggregate inflation dynamics rather poorly.[8] As to the solution under $\varphi_i \leq 1/2$, they show how the empirical process of $\Delta\pi_{it}$ bears very little resemblance to a discounted sum of expected future values of the real marginal cost. More generally, the coefficients attached to the discounted sums in (6) and (7) are not significantly different from zero. They interpret the fact that inflation is unrelated to current and future expected values of the driving term as an explicit rejection of rational forward-looking behavior in price-setting, which is a cornerstone of the New Keynesian paradigm. In the remainder of the paper we test the robustness of these arguments at the sectoral level of aggregation.

3 Data and Preliminary Analysis on the Fit of the NKPC

We use data from the NBER-CES Manufacturing Industry Database (see Bartelsman et al., 1996). This covers 458 manufacturing industries defined at the 4-digit level of disaggregation from 1958 to 1996.[9] Data are available at a yearly frequency and have not been updated over the last decade. However, a clear advantage of this dataset is to provide us with information on both prices and costs at the sectoral level. To enhance the comparison with past evidence on the NKPC, we convert the original series to a quarterly frequency. Quarterly movements in yearly

[7] We do not consider trend inflation, so as to enhance comparability between our study and that of Rudd and Whelan (2006). However, as discussed by Cogley and Sbordone (2008), accounting for trend inflation should imply a diminished importance of lagged inflation.

[8] Their results are robust to the use of alternative proxies for the forcing variable.

[9] This corresponds to the highest level of disaggregation at which data are available. We exclude the "Asbestos Product" industry (SIC 3292) since its time series ends in 1993.

data are estimated through the distribution method of Fernandez (1981), which generalizes the model set out by Chow and Lin (1971).[10]

The labor income share is measured as the total payroll cost over the total shipment value.[11] The income share of intermediate goods is measured as the ratio between the value of the input materials over the total shipment value. Detrended output is computed as the deviation of gross real output from a quadratic trend.[12]

3.1 The Dynamics of Alternative Proxies for the Forcing Variable

Before moving to the econometric analysis, we explore the cyclical properties of the three proxies for the forcing variable and their dynamic cross-correlations with the sector-specific rate of inflation. A key implication of the benchmark NKPC is that inflation should lead x_{it} over the cycle (Fuhrer and Moore, 1995). Moreover, the real marginal cost should be pro-cyclical, so as to imply a counter-cyclical mark-up (Rotemberg and Woodford, 1991).

The left-hand panel of Figure 1a reports the average dynamic cross-correlations of different proxies for the real marginal cost with some leads and lags of inflation, while the right-hand panel reports the number of sectors for which correlations at different points in time are significantly different from zero.[13] To evaluate the cyclical behavior of our cost-based proxies we also report their average dynamic cross-correlations with aggregate detrended output (Figure 1b).

Insert Figure 1 about here

Current detrended output and the labor share co-move positively (negatively) with future (past) inflation. This is at odds with the predictions of the theory, as also Rudd and Whelan (2005a) indicate. However, the picture is reversed when looking at the income share of intermediate goods, which also displays positive contemporaneous correlation with the rate of inflation.[14] The right-hand panel of Figure 1a suggests that such a property results from the number of positive (and significant) cross-correlations with past inflation overcoming the neg-

[10] The exact procedure closely follows Leith and Malley (2007). More details on this method are reported in Appendix A, while Section 5 reports further evidence based on annual data.

[11] We have also considered a proxy based on wage expenses. The analysis is not qualitatively influenced by the specific labor cost proxy we employ.

[12] The literature often relies on the HP filter to extract cyclical components. However, a number of problems arise with such a filtering technique. First, the HP filter is a two-sided filter: thus, its use for present value calculation is unwarranted (see Rudd and Whelan, 2006). Second, it might well be the case that the HP filter extracts spurious cycles at the sectoral level, as emphasized by Harvey and Jaeger (1993).

[13] The dark (light) bars indicate negative (positive) correlations.

[14] Note that the average cross-correlations are rather small, although statistically significant. This reflects strong heterogeneity across sectors, with positive and negative cross-correlations offsetting each other.

ative ones, whereas the reverse holds true when looking at the correlations with the leads of sectoral inflation. Opposite evidence holds for the other proxies. Moreover, Figure 1b shows that the income share of intermediate goods co-moves positively with detrended output, while the labor income share lags it in much the same way as does inflation, which is at odds with the properties of the NK model, as discussed by Rotemberg and Woodford (1991).[15]

Overall, Figure 1 highlights marked discrepancies in the dynamics of the income shares of labor and intermediate goods. Rotemberg and Woodford (1999) indicate the possibility that marginal and average costs manifest different cyclical patterns. Their considerations are especially relevant for the labor input, as labor hoarding, overhead labor and varying effort all induce the labor share to be less pro-cyclical than the real marginal cost. Furthermore, the marginal cost is inaccurately proxied by the labor share in the presence of employment adjustment costs (Bils, 1987), which are traditionally regarded as an important source of inertia in many industrialized countries.[16] By contrast, Basu and Kimball (1997) suggest that the kind of adjustment costs involved in varying the labor input are much less relevant for the intermediate goods. Our preliminary evidence supports this view.

3.2 On the Fit of the NKPC

The aim of this section is to assess the fit of the NKPC. We employ the VAR projection method as first set out by Campbell and Shiller (1987) and applied by Galí and Gertler (1999), Woodford (2001) and Sbordone (2002) to construct measures of fundamental inflation. This involves specifying x_{it} as one of the variables in a sectoral VAR under the following companion form:[17]

[15] Nekarda and Ramey (2009) have also argued against the labor income share based on the fact that it implies a procyclical mark-up, which stands in contrast to the theoretical mechanism underlying the New Keynesian framework.

[16] Nekarda and Ramey (2009) show that a procyclical mark-up arises even when adjustment costs are accounted for.

[17] For each of the proxies we include a different set of sector-specific and aggregate variables in the VAR. When using detrended output the VAR specification includes the labor share and inflation in the same sector, together with detrended aggregate output, the federal funds rate and aggregate inflation. The VAR for the labor income share includes detrended output, price and wage inflation at the sectoral level, together with detrended output, the federal funds rate, inflation and changes in the unit labor cost at the aggregate level. A similar specification is used for the VAR for the intermediate input share: we just replace wage inflation with intermediate inputs inflation at the sectoral level and the change in non-labor input costs at the aggregate level. We then proceed to test the exclusion restriction for each of the variables. For each sector we include only variables displaying evidence of Granger-causality at the 10% critical level. We choose the number of lags consistent with the Hannan and Quinn (1979) criterion, so that we are not able to reject the null of no autocorrelation in the residuals. In principle, the inclusion of aggregate variables should allow us to control for cross-sectional dependence in sectoral data (Pesaran, 2006).

$$\mathbf{v}_{it} = \mathbf{A}_i \mathbf{v}_{it-1} + \mathbf{e}_{it}, \tag{8}$$

where $\mathbf{e}_{it}$ is a vector of *iid* innovations. Equation (8) allows us to express the expected future values of a given variable as a function of the variables observed today. Specifically, if we assume that x_{it} is the first variable in the VAR, for any discount factor κ_i the discounted value of all future realizations of x_{it} is calculated as:

$$E_t \sum_{s=0}^{\infty} \kappa_i^s x_{it+s} = \boldsymbol{\iota}_1' \left(\mathbf{I} - \kappa_i \hat{\mathbf{A}}_i \right)^{-1} \mathbf{v}_{it}, \tag{9}$$

where $\boldsymbol{\iota}_1$ is a selection vector with ones in the first row and zeros elsewhere. Given the discounted sum (9), we can discriminate between alternative specifications of the NKPC by fitting the following least squares regression:

$$\pi_{it} = \alpha_{1i} \boldsymbol{\iota}_1' \left(\mathbf{I} - \kappa_i \hat{\mathbf{A}}_i \right)^{-1} \mathbf{v}_{it} + \alpha_{2i} \pi_{it-1} + \varepsilon_{it}. \tag{10}$$

The purely forward-looking NKPC is obtained by setting $\alpha_{2i} = 0$ and $\kappa_i = \beta$. The hybrid specification with $\varphi_i \leq 1/2$ is obtained by setting $\alpha_{2i} = 1$, while the discount factor is set at the value between 0 and 1 that maximizes the fit of the model. Finally, the hybrid specification with $\varphi_i > 1/2$ requires $\kappa_i = 1$ and leaves us free to estimate the parameter attached to lagged inflation.

Figures 2 to 4 plot (aggregate) inflation against its predicted value for each model of price-setting. For the hybrid specification with $\varphi_i \leq 1/2$ we look at the first-difference in aggregate inflation, $\Delta\pi_t$, as implied by the closed-form solution (6). Every figure consists of three panels, each of them reporting evidence on one of the three proxies.[18] Table 1 reports some goodness-of-fit measures for each NKPC specification, such as the correlation between predicted and actual inflation and the coefficient of determination, R^2. For the hybrid supply schedules we also include the partial coefficient of determination, $\widetilde{R}^2$, which isolates the contribution of the expected discounted sum of future values of the forcing variable to the volatility of inflation, conditional on the contribution of lagged inflation. Column "Agg." reports the correlation between actual and predicted (aggregate) inflation and the average R^2 computed as in Holly

[18] Specifically, aggregate inflation is computed as $\pi_t = \sum_{i=1}^{I} w_i \pi_{it}$, where w_i is the weight of the ith sector and $\sum_{i=1}^{I} w_i = 1$. Each weight reflects the relative importance of the ith sector in the shipment value of all manufacturing sectors.

et al. (2010). Column "Ave." reports the average correlation and the R^2 calculated at the SIC 4-digit level. These statistics are computed for all the manufacturing sectors, as well as for the broad classes of durable (SIC 24, 25,32-38) and non-durable industries (SIC 20-23, 26-31).[19]

Insert Table 1 about here

Insert Figure 2 about here

As suggested by Figure 2, the purely forward-looking NKPC can only account for a minor part of inflation volatility. This is in line with Rudd and Whelan (2005a), who show that this model generally provides a bad fit of aggregate inflation. However, while they observe negative correlation between inflation and the discounted sum of current and future expected values of their driving terms, we find positive and strong correlation, regardless of the specific proxy we employ (see Table 1).[20] Such a discrepancy between the micro and macro evidence reinforces our view on the importance of assessing the fit of the NKPC at a deeper level of disaggregation. It is also interesting to note how, compared to the other proxies, the income share of intermediate inputs does a better job at fitting inflation dynamics, allowing us to (at least partly) track peaks in inflation.

Insert Figure 3 about here

Figure 3 shows that the hybrid version of the model under $\varphi \leq 1/2$ fails to capture the variability in $\Delta\pi_{it}$. Contemporaneous changes in inflation exhibit strong and negative autocorrelation that none of the alternative proxies for x_{it} can replicate.[21] As pointed out by Rudd and Whelan (2006), this is also the case when trying to fit changes in aggregate inflation. In addition, the correlation between the sectoral driving term and $\Delta\pi_{it}$ is often small and statistically insignificant, as confirmed by the partial $\widetilde{R}^2$.

Insert Figure 4 about here

Figure 4 reports the fit of the hybrid model with preponderance of forward-looking price-setting ($\varphi > 1/2$). This model allows us to account for inflation volatility, both at the aggregate

[19] In Appendix B we present analogous evidence at the 2-digit SIC level. For each sector we report the goodness-of-fit measures in the first and second entries of the "fit" column of Tables B1 to B3.

[20] Positive correlation is also appreciated at the 2-digit SIC level (see Appendix B).

[21] It is important to stress that this version of the NKPC fails to capture the variability of both $\Delta\pi_{it}$ and π_{it}. Looking at changes in the rate of inflation allows us to appreciate this weakness of the hybrid model under $\varphi \leq 1/2$, as well as to enhance the comparison with Rudd and Whelan (2006). Additional evidence on the fit of the level of fundamental inflation is available from the authors upon request.

and sectoral level: this comes as no surprise, given that inflation is regressed on its own lag. To appreciate the actual contribution of the forcing variable, we look at the average partial coefficient of determination: the resulting values always lie below 2%, suggesting that most of the variability in the dependent variable is indeed explained by the lagged inflation term. In agreement with the evidence reported for the purely forward-looking specification, using the cost of intermediate goods returns goodness-of-fit statistics that are slightly better than those obtained under alternative proxies.

To sum up, the discounted sum of future values of the forcing variable can explain at best a small part of sectoral inflation variability. The purely forward-looking NKPC reflects a limited but (relatively) important impact of x_{it} on current inflation. Even though a high correlation between actual and predicted inflation is appreciated, this version of the price-setting model falls short in accounting for inflation volatility. When a lag of the rate of inflation is included, the hybrid model with preponderance of forward-looking price-setters tracks inflation dynamics quite closely. However, the fit due to current and future expected realizations of the forcing variable diminishes significantly. Furthermore, the income share of intermediate goods generally seems to outperform other empirical measures of x_{it}.

4 Reduced-form GMM Estimation

The approach pursued in the previous section does not provide us with the tools necessary to make statistical inference about the model's parameters. In fact, little or no guidance is given about the statistical significance of the impact exerted by the discounted sum of current and expected values of the forcing variable. Moreover, in spite of the important differences between alternative proxies for x_{it} in terms of their cyclical properties, the Campbell-Shiller approach cannot effectively discriminate among them in terms of their capability to act as drivers of inflation dynamics. To overcome these limitations we follow Rudd and Whelan (2005b, 2006) and estimate the closed-form solutions to different dynamic specifications of the NKPC.

A closed-form solution encompassing various specifications for the NKPC can be written as:

$$\pi_{it} = \alpha_{1i} E_t \sum_{s=0}^{\infty} \kappa_i^s x_{it+s} + \alpha_{2i} \pi_{it-1} + \varepsilon_{it}. \tag{11}$$

To make this expression tractable, the infinite discounted sum of the expected future values of the forcing variable can be approximated as:

$$E_t\left[\pi_{it+K+1} - \alpha_{2i}\pi_{it+K}\right] = \alpha_{1i}\kappa_i^{-(K+1)} \sum_{s=K+1}^{\infty} \kappa_i^s E_t x_{it+s}. \tag{12}$$

The orthogonality conditions for the GMM estimation of the reduced-form parameters read as:

$$E_t\left[\left(\pi_{it} - \alpha_{2i}\pi_{it-1} - \alpha_{1i}\sum_{s=0}^{K}\kappa_i^s x_{it+s} - \kappa_i^{K+1}\left(\pi_{it+K+1} - \alpha_{2i}\pi_{it+K}\right)\right)\mathbf{z}_{it}\right] = 0, \tag{13}$$

where $\mathbf{z}_{it}$ denotes the set of instruments.

We are now ready to take (11) to the data. To this end we set $K = 12$.[22] The set of instruments differs for each sector and includes all the variables which are statistically significant at the 10% level in the first step estimation.[23] Every instrument set fulfills the relevance criterion of Stock and Yogo (2002).

Insert Table 2 about here

Table 2 reports the results from the estimation of the purely forward-looking NKPC and the hybrid specifications under different degrees of forward-lookingness. The purely forward-looking NKPC can be recovered from (11) by setting $\alpha_{2i} = 0$, $\alpha_{1i} = \gamma_i$ and $\kappa_i = \beta$. For each of the three alternative proxies we report the mean-group estimates (MG hereafter)[24] of γ (denoted by $\bar{\gamma}$) and the number of sectors for which the coefficient associated with the forcing variable is statistically significant and positive. The first result emerging from the analysis at the aggregate level is that $\bar{\gamma}$ is statistically significant, regardless of the variable employed to proxy x_{it}. However, the estimated parameter is negative when we use either detrended output or the labor income share, which is at odds with the predictions of the theory. Conversely, using the income share of intermediate goods delivers a statistically significant and positive MG estimate. A similar picture emerges at the sectoral level: in this case the number of significant and positive estimates of γ_i is about three times larger when using the cost of intermediate

[22] The results reported in the remainder of this section are robust to different choices of K.

[23] The instrument set for the model with detrended output includes five lags of sectoral detrended output, the labor share, inflation, as well as detrended aggregate output, PPI inflation and the federal funds rate. When the labor share is used to proxy the forcing variable, the instrument set also includes wage inflation at the sectoral level and the growth rate of the unit labor cost at the aggregate level. Similarly, for the model based on the cost of intermediate goods the original instrument set is expanded, so as to include price inflation of the sector-specific input materials and changes in unit non-labor costs at the aggregate level.

[24] The Mean Group heterogeneous estimator introduced by Pesaran and Smith (1995) involves estimating the NKPC for each sector separately and calculating coefficients' means. This provides us with consistent estimates of the average NKPC coefficients.

goods, compared to those obtained with the other two proxies. Furthermore, the MG estimates for the broadly defined sectors producing durables and non-durables are both positive, although the estimated coefficient for the non-durables sector is not statistically different from zero (the p-value is approximately 14%). Overall, the forward looking version of the model reflects a small, yet statistically significant impact of the sum of current and expected future values of the income share of intermediate goods.

We next focus on the reduced-form expressions of (6) and (7). The hybrid NKPC relationship with preponderance of backward-looking price setters ($\varphi_i \leq 1/2$) imposes $\alpha_{2i} = 1$, $\alpha_{1i} = \lambda_{1i}$ and $\kappa_i = \lambda_{2i}$ in (11):

$$\Delta\pi_{it} = \lambda_{1i} E_t \sum_{s=0}^{\infty} \lambda_{2i}^s x_{it+s} + \varepsilon_{it}. \tag{14}$$

The MG estimates for all manufacturing sectors are positive and statistically significant. At a first glance this result might be interpreted as supporting the hybrid model with $\varphi \leq 1/2$. However, a closer look at the sectoral estimates reveals that the coefficients are both significant and positive in a very limited number of cases.[25]

The hybrid relationship with preponderance of forward-looking price-setting ($\varphi_i > 1/2$) constrains the discount parameter $\kappa_i = 1$. In this case the empirical validity of the NKPC relies on the significance of $\mu_{1i} (= \alpha_{1i})$, which accounts for the relative statistical contribution of future realizations of the forcing variable, while $\mu_{2i} (= \alpha_{2i})$ captures the dependence of current inflation from its own lag:

$$\pi_{it} = \mu_{1i} E_t \sum_{s=0}^{\infty} x_{it+s} + \mu_{2i}\pi_{it-1} + \varepsilon_{it}. \tag{15}$$

The estimation results mirror those obtained from the purely forward-looking version of the model. For every proxy of the forcing variable the associated coefficient is statistically significant. However, the MG estimates are negative when we use either detrended output or the labor share, while a positive and significant estimate of $\bar{\mu}_1$ is observed when employing the cost of intermediate goods. In the latter case the sectoral NKPC cannot be rejected for 141 sectors, a value which is between two to five times larger than what we appreciate when using the output gap and the labor share, respectively. As to the MG estimates for the broadly defined sectors producing durables and non-durables, these are still positive, although the estimated coefficient

[25] At best, coefficients λ_{1i} and λ_{2i} are both significant and positive for just 67 (out of 458) sectors in the model with detrended output.

for the durables sector is not statistically different from zero.[26] By contrast, using other proxies for the forcing variable returns negative estimates.

To sum up, proxying the real marginal cost with a measure based on the cost of intermediate goods delivers MG estimates which are often statistically significant and economically meaningful.[27] On average, the NKPC represents a valid benchmark to model inflation dynamics. This argument can be reinforced by taking a closer look at the sectoral estimates. In fact, in 225 sectors the estimated parameters of at least one of the NKPC specifications are significant and present the correct sign.[28] In addition, for a vast majority of sectors (i.e., 375) at least one of the three models of price-setting delivers estimates with the correct sign.

4.1 Heterogeneity and Biased GMM Estimates at the Aggregate Level

Imbs et al. (2007) and Altissimo et al. (2009) point out that the data aggregation process can explain a high proportion of the persistence in aggregate inflation. As a general principle, neglecting sectoral heterogeneity implies that the error term in the regression with aggregate data is partially affected by sectoral regressors, so that aggregate estimates are biased. The GMM estimates presented in the previous section are in line with this view, as the mean of the autoregressive parameters in the hybrid models with $\varphi > 1/2$ is significant but rather small in absolute value. This stands in contrast to the evidence of Rudd and Whelan (2006), as their aggregate study attributes a prominent role to lagged inflation, while current and expected future values of the forcing variable are almost irrelevant to inflation dynamics. This subsection is explicitly aimed at understanding whether aggregation may play a role in the context of Rudd and Whelan (2006).

We first rely on a numerical example that proves to be rather informative on the potential direction and magnitude of the biases in the GMM estimation of the aggregate NKPC. As in Imbs et al. (2007), we set up a two-sector model:

$$\pi_{it} = \varphi_i E_t \pi_{it+1} + (1-\varphi_i)\,\pi_{it-1} + \gamma_i x_{it} + \eta_{it}, \; 0 \le \varphi_i \le 1, \tag{16}$$

$$x_{it} = \rho_i x_{it-1} + u_{it}, \quad i = 1, 2. \tag{17}$$

[26] Furthermore, the statistically significant MG estimates of this coefficient at the 2-digit level are always positive when we use the proxy based on the cost of intermediate goods (see Appendix B).

[27] Although the estimated impact of the forcing variable may generally appear rather low, Section 4.2 shows that the implied frequencies of price changes are in line with the micro-based estimates of Nakamura and Steinsson (2008).

[28] It is also worth mentioning that in 167 cases at least one of the alternative hybrid models provides a good representation of inflation dynamics, implying that only for 26 sectors we are not able to discriminate between the two hybrid models.

We use simulation exercises to evaluate the relative impact of the dispersion in φ_i and γ_i on their aggregate counterparts, φ and γ. To this end, we simulate the solution to (16)-(17) under rational expectations for each sector separately. We then aggregate (with equal weights) over sectors and the resulting series are used to estimate the relevant closed-form solution. In the remainder of this subsection we will mostly focus on the hybrid model with preponderance of forward-looking price setters, as the analysis so far indicates this benchmark as the one providing the best description of average sectoral price-setting.[29]

Average inflation ($\bar{\pi}_t = \sum_{i\in(1,2)} \pi_{it}/2$) evolves in accordance with:

$$\bar{\pi}_t = \mu_1 E_t \sum_{s=0}^{\infty} \bar{x}_{t+s} + \mu_2 \bar{\pi}_{t-1} + \varepsilon_t.$$

We set $\rho_1 = \rho_2 = 0.9$ and $\sigma_\eta^2/\sigma_u^2 = 1$, where σ_η^2 and σ_u^2 are the variances of η_{it} and u_{it}, respectively. As to the remaining parameters, $\varphi_1 = 0.75$ and γ_1 is such that $\theta_1 = 0.6$, while for the other sector we draw φ_2 and θ_2 from the intervals $[0.6, 0.9]$ and $[0.3, 0.9]$.

Insert Figure 5 about here

Figure 5 reports the biases associated with the estimates of μ_1 and μ_2. These hint that $\hat{\mu}_1$ ($\hat{\mu}_2$) displays a negative (positive) bias, which amounts to say that the estimation with aggregate data tends to under-estimate the impact of the discounted sum of the forcing variable, while over-estimating the impact of the lagged inflation term.[30] Furthermore, the bias in $\hat{\mu}_1$ tends to decrease when γ_2 is relatively larger, i.e. when sectoral prices are relatively more flexible. Overall, these results are in line with Imbs et al. (2007) and hint that aggregation may play a role in the analysis of Rudd and Whelan (2006).

To understand whether aggregation is relevant in the sample under scrutiny, we estimate μ_1 and μ_2 with data obtained by aggregating variables at the manufacturing level.[31] We then compare $\hat{\mu}_1$ and $\hat{\mu}_2$ to the sectoral estimates. Figure 6 returns evidence in line with our computational exercise. The MG estimate of the coefficient associated with past inflation is considerably lower than that obtained with aggregate data. Most importantly, the MG estimate of μ_1 is twice

[29] The results for alternative NKPC models are available from the authors upon request.

[30] The latter result is in line with Granger (1980), who shows that if N stationary $AR(1)$ series are aggregated and the autoregressive parameters can take on any value in a given interval, the aggregated data may even display long-memory behavior.

[31] Aggregate variables are obtained as weighted averages of their sectoral counterparts, with weights reflecting the relative importance of a given sector in the shipment value of all manufacturing sectors. Computing simple averages of the sectoral variables would return similar results. The forcing variable is proxied by the income share of intermediate goods.

as large as the value estimated with aggregate data (i.e., 0.0038 vs. 0.0015), with the latter being not statistically significant at the 10% level. Hence, it becomes clear that the analysis with aggregate data would lead us to reject the NKPC as a plausible paradigm of price-setting and overplay the role of lagged inflation, as otherwise documented by Rudd and Whelan (2006).

Insert Figure 6 about here

4.2 Heterogeneity in Sectoral Price Stickiness

In what follows we document further evidence in support of our estimates of sectoral price rigidity, comparing them with the implied estimates obtained by Nakamura and Steinsson (2008) from highly disaggregated U.S. data.[32]

Insert Table 3 about here

Table 3 reports the average of our sectoral implied Calvo probabilities,[33] together with the minimum and maximum sectoral estimates and those implied by micro-based evidence reported by Nakamura and Steinsson.[34] As in Blinder et al. (1998) and Nakamura and Steinsson (2008), finished-goods producer prices tend to exhibit substantial rigidity. On average, our estimates tend to agree with those reported in the benchmark study: the micro-based estimates generally fall within the minimum and maximum bounds implied by both versions of the hybrid NKPC.[35] The only exceptions are represented by "fuels, related products and power" and "transportation equipment", two sectors characterized by low price rigidity. Therefore, it comes as no surprise that the NKPC does not represent a plausible model of price-setting for these industries. As to remaining sectors, we have some examples with average estimates of price rigidity being very close to those of Nakamura and Steinsson. For instance, in the model with $\varphi \leq 0.5$ one could note a close resemblance in the average stickiness of the following sectors: "chemicals and allied products" and "non-metallic mineral products". Otherwise, the hybrid NKPC with $\varphi > 0.5$ returns similar estimates in the following cases: "textile products and apparel", "rubber and plastic products" and "metals and metal products". This said, we should stress that no

[32] We consider Panel A in Table 12 from the appendix of Nakamura and Steinsson (2008), as it refers to the period 1988-1997, which partly overlaps with our time window. Their micro-based estimates of price rigidity are reported in terms of frequency of adjustments, from which durations may be computed.

[33] These are retrieved from the GMM estimation of different dynamic specifications of the NKPC.

[34] Note that our computation of the Calvo probabilities is only feasible for those sectors characterized by a positive estimate of the slope of the NKPC. Moreover, we only consider the estimates obtained by proxying x_{it} with the intermediate input income share. Additional results are available, upon request, from the authors.

[35] Bouakez et al. (2009a) also obtain estimates which are in line with Nakamura and Steinsson (2008) from a fully-fledged DSGE model that accounts for cross-industry flows of input materials.

discrimination can actually be made between the two versions of hybrid NKPC in terms of their relative concordance with the micro-based evidence. Nevertheless, it is worth observing that the implied estimates based on the hybrid NKPC with preponderance of backward-looking price setters display higher dispersion around their sectoral means and their distribution tends to appear right-skewed. By contrast, the estimates obtained under the purely forward-looking NKPC and the hybrid version with $\varphi > 1/2$ display lower dispersion around their sectoral means and generally are very similar.

5 Robustness

We have shown that sectoral inflation dynamics can often be tracked by combining the income share of intermediate goods as a proxy for the real marginal cost with a hybrid NKPC reflecting preponderance of forward-looking price setters. Within this setting the expected discounted sum of future values of the forcing variable is shown to act as an effective driving force of inflation dynamics. This section is aimed at testing the robustness of this result. We first relax the Cobb-Douglas hypothesis and consider a CES production technology, so as to account for the possibility of a non-unit elasticity of substitution between intermediate and primary inputs. We then estimate the hybrid NKPC with preponderance of forward-looking price setters on annual data, so as to ensure that our results are not affected by the interpolation from yearly to quarterly data.

5.1 A CES Production Function

When computing a proxy for driving term an important correction relates to the possibility that the elasticity of substitution between intermediate and primary inputs is different from one, as argued by Basu (1995) and Rotemberg and Woodford (1996). In fact, a generic CES production function implies that the real marginal cost is also determined by the relative price of intermediate goods:[36]

$$RMC_{it}(z) = \frac{1}{1-\alpha_i}\left[\frac{P_{it}^M M_{it}(z)}{P_{it} Y_{it}(z)}\right]^{\varrho_i}\left(\frac{P_{it}^M}{P_{it}}\right)^{1-\varrho_i}, \tag{18}$$

where $\varrho_i \geq 0$ is the inverse of the elasticity of substitution between input materials and labor. Under the assumption of within sector homogeneity we can express the sectoral real marginal

[36] See, e.g., Rotemberg and Woodford (1999) and Leith and Malley (2007).

cost in log-linear terms:

$$rmc_{it} = \varrho_i s_{it}^M + (1 - \varrho_i)\, q_{it}^M - \log\left(\frac{1}{1 - \alpha_i}\right), \tag{19}$$

with q_{it}^M denoting the logarithm of the relative price of intermediate inputs in the ith sector. The closed-form solution to the hybrid NKPC with $\varphi_i > 0.5$ can be written as

$$\pi_{it} = \psi_{1i} E_t \sum_{s=0}^{\infty} \left(\varrho_i s_{it+s}^M + (1 - \varrho_i)\, q_{it+s}^M\right) + \psi_{2i}\pi_{it-1} + \varepsilon_{it}. \tag{20}$$

Insert Table 4 about here

Table 4 reports the results from the estimation of (20). Once again, for all manufacturing sectors we obtain a significant MG estimate of the reduced-form parameter associated with the expected future realizations of the real marginal cost ($\bar{\psi}_1$). We should also note that the estimates of both ψ_{1i} and ψ_{2i} are generally very close to those of μ_{1i} and μ_{1i} obtained under a Cobb-Douglas production technology, a result that supports the findings reported in Section 4. Moreover, the average estimates of the elasticity of substitution are rather small, as a result of including few sectors with large estimates of ϱ_i. In fact, it should be noted that the $\hat{\varrho}_i$'s distribution is heavily right-skewed, as $\hat{\varrho}_i$ is lower than one (two) in 233 (314) sectors.

5.2 Evidence with Annual Data

We now fit the closed-form solution to the hybrid model with $\varphi > 1/2$ on the original annual data.[37] For each proxy we consider the same set of instruments as in the analysis of quarterly data and set $K = 3$ in (13).

Insert Table 5 about here

The estimation results are reported in Table 5. Compared to the estimates obtained with quarterly data, the coefficient attached to the autoregressive component is lower, while that associated with future realizations of the real marginal cost increases. Intuitively, both changes are consistent with the implications of the underlying model of price-setting.[38] Overall, these results confirm the good performance of the hybrid NKPC with the intermediate input share

[37] The results for alternative NKPC models are similar to those obtained with quarterly data and can be obtained from the authors upon request.

[38] Specifically, calibrating the model at a yearly frequency implies a smaller autoregressive parameter and a higher forcing variable coefficient, compared to the values consistent with a quarterly calibration.

proxying the real marginal cost. Moreover, note that $\bar{\mu}_1$ is also significant when distinguishing between durable and non-durable goods sectors, while $\hat{\mu}_{1i}$ is significant and positive for 247 sectors.

6 Conclusions

Recent evidence casts serious doubts on the suitability of the NKPC to account for the dynamics of aggregate inflation. Jeremy Rudd and Karl Whelan have extensively tested both purely forward-looking and hybrid models of price setting concluding that the type of rational forward-looking behavior embodied by the NKPC finds little support in the data.

In this paper we argue that imposing the NKPC structure on aggregate data, as most of the existing empirical contributions have done, may entail a fundamental fallacy, which amounts to assuming that the hypotheses underlying price-setting behavior at the micro-level can be innocuously transposed to the aggregate. In light of this, we complement the analysis of Rudd and Whelan and explore the coherence of their arguments in the context of New Keynesian models of sectoral inflation.

We provide evidence in support of the forward-lookingness characterizing the New Keynesian paradigm of price-setting, showing that current and expected future values of the income share of input materials act as an effective driving force of inflation. Unlike other empirical measures of the forcing variable, the cost of intermediate goods displays dynamic properties in line with the key predictions of the New Keynesian theory. In fact, combining this proxy with a hybrid NKPC featuring preponderance of forward-looking price setters closely predicts inflation dynamics in a large number of sectors. Moreover, the average estimates of the parameters accounting for the impact of past inflation and the forcing variable are statistically significant and economically meaningful.

On a more general note, this paper emphasizes the importance of testing key macroeconomic relationships at a deeper level of disaggregation. This allows the researcher to account for the degree of heterogeneity underlying economic decisions and, from a purely statistical perspective, various other problems that may arise from the data aggregation process (Imbs et al., 2011). As to the specific case we explore, showing that the cost of intermediate goods acts as an effective driver of inflation dynamics emphasizes the need of including input materials into multi-sector dynamic general equilibrium models. This should help both at providing a more rigorous description of the underlying structure of the economy (Bouakez et al., 2008 and 2009) and formulating policy prescriptions that account for the role of cross-industry flows of input materials in propagating shocks to the economy (Petrella and Santoro, 2011).

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TABLE 1: Fit of the NKPC								
A. PURELY FORWARD-LOOKING NKPC								
		Detrended Output		Labor Share		Inter. Input Share		
		Agg.	Ave.	Agg.	Ave.	Agg.	Ave.
All Manufacturing	Corr.	0.6648	0.2138	0.5180	0.1752	0.7283	0.2203
	R^2	0.0717	0.0672	0.0731	0.0485	0.0611	0.0716
Non-Durables Sectors	Corr.	0.5131	0.2243	0.4189	0.1877	0.5956	0.2067
	R^2	0.0852	0.0732	0.0899	0.0549	0.0588	0.0626
Durables Sectors	Corr.	0.6464	0.2038	0.6373	0.1638	0.7631	0.2320
	R^2	0.0501	0.0624	0.0498	0.0426	0.0658	0.0782
B. HYBRID NKPC ($\varphi \leq 1/2$)							
		Detrended Output		Labor Share		Inter. Input Share	
		Agg.	Ave.	Agg.	Ave.	Agg.	Ave.
All Manufacturing	Corr.	0.2234	0.0953	0.0616	0.0462	0.1256	0.0518
	$\widetilde{R}^2$	0.0138	0.0123	0.0058	0.0030	0.0066	0.0039
Non-Durables Sectors	Corr.	0.1761	0.1076	0.0546	0.0506	0.1011	0.0508
	$\widetilde{R}^2$	0.0158	0.0157	0.0075	0.0037	0.0067	0.0037
Durables Sectors	Corr.	0.1650	0.0858	0.0415	0.0430	0.2049	0.0516
	$\widetilde{R}^2$	0.0094	0.0098	0.0028	0.0025	0.0062	0.0039
C. HYBRID NKPC ($\varphi > 1/2$)							
		Detrended Output		Labor Share		Inter. Input Share	
		Agg.	Ave.	Agg.	Ave.	Agg.	Ave.
All Manufacturing	Corr.	0.8223	0.6548	0.8191	0.6544	0.8368	0.6570
	R^2	0.3704	0.4431	0.3703	0.4424	0.3685	0.4459
	$\widetilde{R}^2$		0.0086		0.0068		0.0117
Non-Durables Sectors	Corr.	0.7184	0.6314	0.7150	0.6312	0.7383	0.6324
	R^2	0.3473	0.4181	0.3461	0.4171	0.3408	0.4187
	$\widetilde{R}^2$		0.0102		0.0089		0.0116
Durables Sectors	Corr.	0.8030	0.6703	0.8007	0.6699	0.8165	0.6734
	R^2	0.4001	0.4595	0.4018	0.4589	0.4050	0.4639
	$\widetilde{R}^2$		0.0075		0.0051		0.0118

Notes: Table 1 reports some goodness-of-fit measures for different specifications of the NKPC and three different proxies for the forcing variable. We consider both the correlation between aggregate and predicted inflation, as well as the R^2. Specifically, column "Agg." reports the correlation between actual and predicted aggregate inflation, as well as the R^2 of the MG estimator computed as in Holly et al. (2008). Column "Ave." reports the average correlation and the R^2 calculated at the SIC 4-digit level of aggregation. Furthermore, for the hybrid versions of the NKPC (panels B and C) we include the partial coefficient of determination, $\widetilde{R}^2$, which isolates the contribution of the expected discounted sum of future values of the forcing variable to the volatility of inflation, conditional on the contribution of lagged inflation.

TABLE 2: GMM Estimation						
A. PURELY FORWARD-LOOKING NKPC						
	Detrended Output		Labor Share		Inter. Input Share	
	$\overline{\gamma}$		$\overline{\gamma}$		$\overline{\gamma}$	
All Manufacturing	-0.0068***		-0.0052***		0.0063***	
	(0.0015)		(0.0008)		(0.0020)	
	63		47		174	
Non-Durables Sectors	-0.0112***		-0.0046***		0.0047	
	(0.0033)		(0.0015)		(0.0032)	
	28		23		53	
Durables Sectors	-0.0044***		-0.0058***		0.0065**	
	(0.0011)		(0.0010)		(0.0025)	
	31		22		112	
B. HYBRID NKPC ($\varphi \leq 1/2$)						
	Detrended Output		Labor Share		Inter. Input Share	
	$\overline{\lambda}_1$	$\overline{\lambda}_2$	$\overline{\lambda}_1$	$\overline{\lambda}_2$	$\overline{\lambda}_1$	$\overline{\lambda}_2$
All Manufacturing	0.0293***	0.1944***	0.0200***	0.1228***	0.0130*	0.1285***
	(0.0035)	(0.0337)	(0.0030)	(0.0335)	(0.0071)	(0.0333)
	67		44		39	
Non-Durables Sectors	0.0393***	0.2466***	0.0262***	0.1564***	0.0155	0.1752***
	(0.0065)	(0.0518)	(0.0057)	(0.0520)	(0.0109)	(0.0544)
	22		21		18	
Durables Sectors	0.0227***	0.1657***	0.0165***	0.0981**	0.0088	0.0860**
	(0.0040)	(0.0458)	(0.0034)	(0.0454)	(0.0100)	(0.0435)
	44		22		17	
C. HYBRID NKPC ($\varphi > 1/2$)						
	Detrended Output		Labor Share		Inter. Input Share	
	$\overline{\mu}_1$	$\overline{\mu}_2$	$\overline{\mu}_1$	$\overline{\mu}_2$	$\overline{\mu}_1$	$\overline{\mu}_2$
All Manufacturing	-0.0050	0.5470***	-0.0010	0.5753***	0.0038***	0.5502***
	(0.0032)	(0.0114)	(0.0007)	(0.0106)	(0.0014)	(0.0109)
	74	422	34	438	141	436
Non-Durables Sectors	-0.0118	0.5125***	-0.0002	0.5711***	0.0024	0.5563***
	(0.0074)	(0.0194)	(0.0010)	(0.0171)	(0.0027)	(0.0181)
	25	168	22	181	47	174
Durables Sectors	-0.0007	0.5729***	-0.0016	0.5873***	0.0043***	0.5459***
	(0.0015)	(0.0140)	(0.0011)	(0.0134)	(0.0015)	(0.0139)
	42	238	11	241	87	246

Notes: Table 2 summarizes the estimation of the closed-form solutions to different specifications of the NKPC. For the different proxies of the forcing variable the table reports the mean group estimates of the coefficients (denoted by the "-" symbol) and the associated standard error (in parenthesis), computed through the non-parametric estimator proposed by Pesaran and Smith (1995); ***/**/* denotes significant at 1/5/10 percent level, respectively. For each specification we also report the number of sectors for which the sectoral estimates are significant and present the sign predicted by the theory. This means that for the purely forward-looking specification we report the number of sectors for which $\hat{\gamma}_i$ is positive and significant. For the hybrid version of the model with $\varphi \leq 1/2$ we report the number of sectors for which both $\hat{\lambda}_{1i}$ and $\hat{\lambda}_{2i}$ are positive and statistically significant. Finally, for the hybrid version with $\varphi > 1/2$ we report the number of sectors for which $\hat{\mu}_{1i}$ is significant and positive, while for $\hat{\mu}_{2i}$ we report the number of cases in which it is significantly different from zero, regardless of its sign. The total number of sectors is 458, with 187 sectors producing non-durables and 253 sectors involved in the production of durables.

TABLE 3: Implied Calvo Probabilities

	NS	FWD-LOOKING NKPC	HYBRID NKPC ($\varphi \leq 1/2$)	HYBRID NKPC ($\varphi > 1/2$)
Processed Foods and Feeds/Farm Products	0.6165	0.8540	0.7681	0.8409
		[0.6203 - 0.9771]	[0.1812 - 0.9862]	[0.5783 - 0,9752]
Textile Products and Apparel	0.8777	0.8802	0.7329	0.8863
		[0.7122 - 0.9816]	[0.1469 - 0.9951]	[0.7842 - 0,9647]
Hides, Skins, Leather, and Related Products	0.7783	0.8669	0.8136	0.8800
		[0.7927 - 0.9280]	[0.7023 - 0.8970]	[0.7768 - 0,9605]
Fuels and Related Products and Power	0.0000	0.8183	0.9055	0.7730
		[0.7071 - 0.9046]	[0.8602 - 0.9550]	[0.7492 - 0,8253]
Chemicals and Allied Products	0.7775	0.9011	0.7515	0.8894
		[0.7324 - 0.9755]	[0.2969 - 0.9714]	[0.6964 - 0,9575]
Rubber and Plastic Products	0.8623	0.8523	0.7979	0.8425
		[0.8156 - 0.9066]	[0.3400 - 0.9830]	[0.7245 - 0,9664]
Lumber and Wood Products	0.6842	0.8239	0.7764	0.8613
		[0.6326 - 0.9328]	[0.4734 - 0.9665]	[0.6835 - 0,9632]
Pulp, Paper and Allied Products	0.8302	0.8969	0.8158	0.8855
		[0.8137 - 0.9591]	[0.3750 - 0.9530]	[0.7804 - 0,9904]
Metals and Metal Products	0.8511	0.8497	0.7259	0.8508
		[0.7031 - 0.9787]	[0.0435 - 0.9736]	[0.6756 - 0,9779]
Machinery and Equipment	0.8604	0.9002	0.8064	0.9101
		[0.7028 - 0.9787]	[0.1863 - 0.9789]	[0.7763 - 0,9744]
Furniture and Household Durables	0.8197	0.9111	0.7585	0.8798
		[0.8709 - 0.9545]	[0.6245 - 0.9207]	[0.7682 - 0,9583]
Nonmetallic Mineral Products	0.8235	0.8985	0.8248	0.8920
		[0.8400 - 0.9824]	[0.4573 - 0.9619]	[0.8064 - 0,9733]
Transportation Equipment	0.0884	0.9170	0.8062	0.8981
		[0.7644 - 0.9927]	[0.5148 - 0.9593]	[0.8157 - 0,9671]
Miscellaneous Products	0.6808	0.8556	0.7927	0.8453
		[0.7289 - 0.9702]	[0.3198 - 0.9674]	[0.7558 - 0,9686]

Notes: Table 3 reports the Calvo probabilities implied by the micro-based evidence of Nakamura and Steinsson (NS, 2008) and the implied probabilities from our GMM estimation of different dynamic NKPC specifications. For each of our average estimates we also report the minimum/maximum sectoral estimates (square brackets). Recall that $\theta_i = 1 - 1/D_i$, where D_i stands for the expected price duration. In turn, the mean durations for producer prices are computed as the inverse of the monthly frequencies of price changes for Major Industries, divided by 3 to express them in quarters.

TABLE 4: Estimation of the hybrid NKPC with $\varphi > 0.5$ and a CES production function			
	$\overline{\psi}_1$	$\overline{\psi}_2$	$\overline{\varrho}$
All Manufacturing	0.0035^{**}	0.5588^{***}	14.9246^{***}
	(0.0018)	(0.0107)	(1.3597)
	137	441	102
Non-Durables Sectors	0.0045^{*}	0.5307^{***}	14.6298^{***}
	(0.0025)	(0.0183)	(2.0812)
	55	176	45
Durables Sectors	0.0027	0.5809^{***}	15.8421^{***}
	(0.0027)	(0.0127)	(1.9067)
	77	249	55

Notes: Table 4 reports the mean group estimate of the coefficients in the closed-form solution to the hybrid NKPC with $\varphi > 0.5$. The relevant proxy for the real marginal cost is computed from the cost of intermediate goods. The associated standard errors (in parenthesis) are calculated through the non-parametric estimator of Pesaran and Smith (1995); $^{***}/^{**}/^{*}$ denotes significant at 1/5/10 percent level, respectively. Under the standard errors associated with $\hat{\psi}_{1i}$ we report the number of SIC 4-digit sectors for which the estimates are positive and significant at the 10% level; for $\hat{\psi}_{2i}$ we only report the number of sectors for which we obtain significant estimates, regardless of their sign. Finally, for $\hat{\varrho}_i$ we report the number of sectors for which the coefficients are statistically different from one 1, i.e. the Cobb-Douglas benchmark.

TABLE 5: GMM ESTIMATION OF THE HYBRID NKPC ($\varphi > 1/2$) (annual data)						
	Detrended Output		Labor Share		Inter. Input Share	
	$\overline{\mu}_1$	$\overline{\mu}_2$	$\overline{\mu}_1$	$\overline{\mu}_2$	$\overline{\mu}_1$	$\overline{\mu}_2$
All Manufacturing	-0.0217***	0.3626***	-0.0307***	0.3379***	0.0263***	0.3489***
	(0.0043)	(0.0162)	(0.0024)	(0.0108)	(0.0046)	(0.0108)
	120	390	36	438	247	437
Non-Durables Sectors	-0.0348***	0.2505***	-0.0370***	0.2590***	0.0397***	0.2621***
	(0.0093)	(0.0241)	(0.0048)	(0.0161)	(0.0083)	(0.0165)
	44	148	17	173	96	173
Durables Sectors	-0.0132***	0.4382***	-0.0268***	0.3964***	0.0152***	0.4140***
	(0.0036)	(0.0213)	(0.0024)	(0.0140)	(0.0052)	(0.0132)
	72	226	17	248	138	247

Notes: Table 5 summarizes the estimation of the closed-form solution to the hybrid model with $\varphi > 1/2$ and original annual data. Further details are provided in the notes to Table 2.

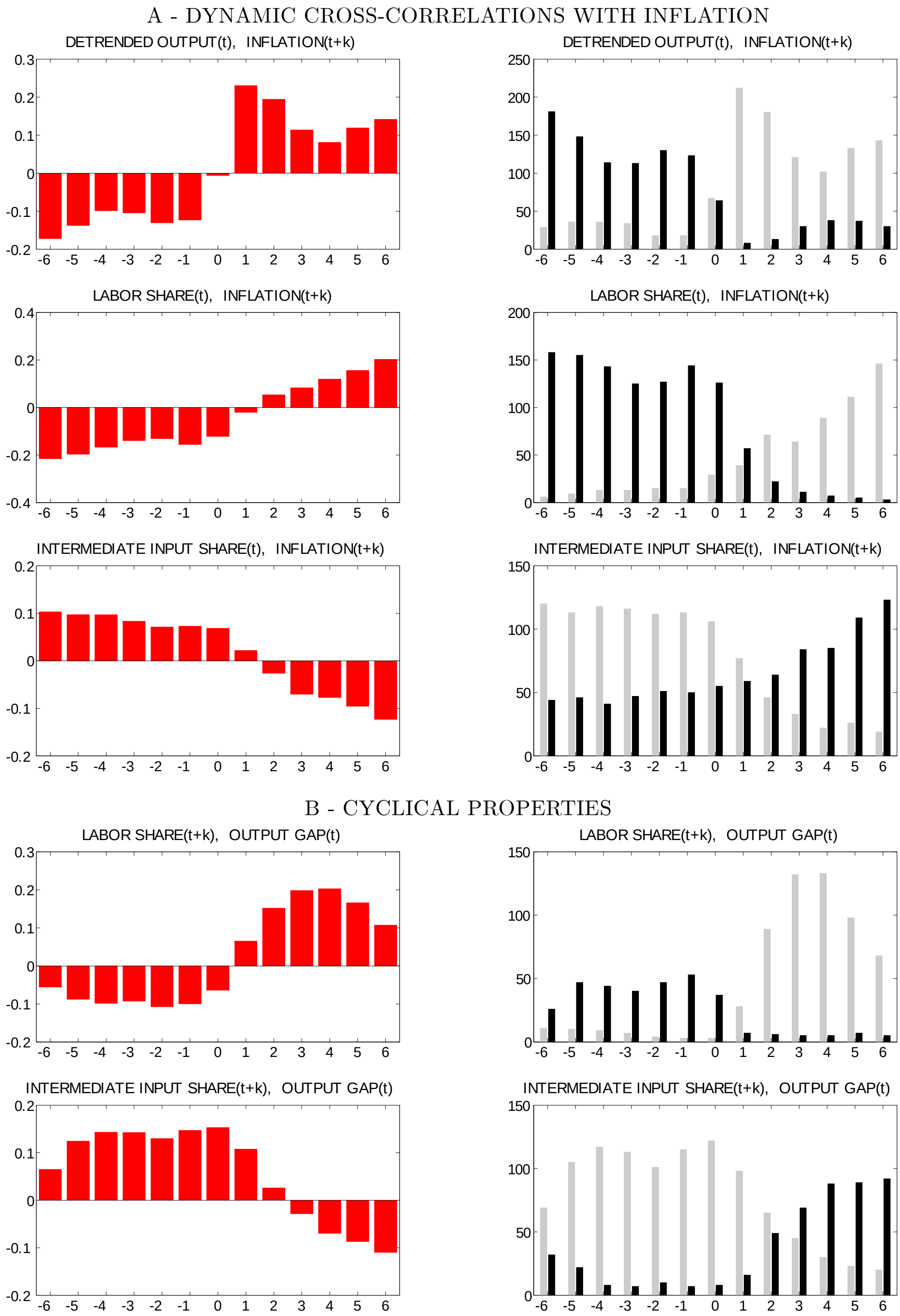

FIGURE 1: Dynamic cross-correlations. The left-hand panel of the figure reports: A. the (sectoral) average dynamic cross-correlations of detrended output, labor share and income share of intermediate goods with different leads and lags of sectoral inflation; B. the (sectoral) average dynamic cross-correlations between the income share of intermediate goods and the labor share with (aggregate) detrended output. In the right-hand panel we report the number of sectors for which the correlation is significant: the light (dark) bars indicate positive (negative) correlations.

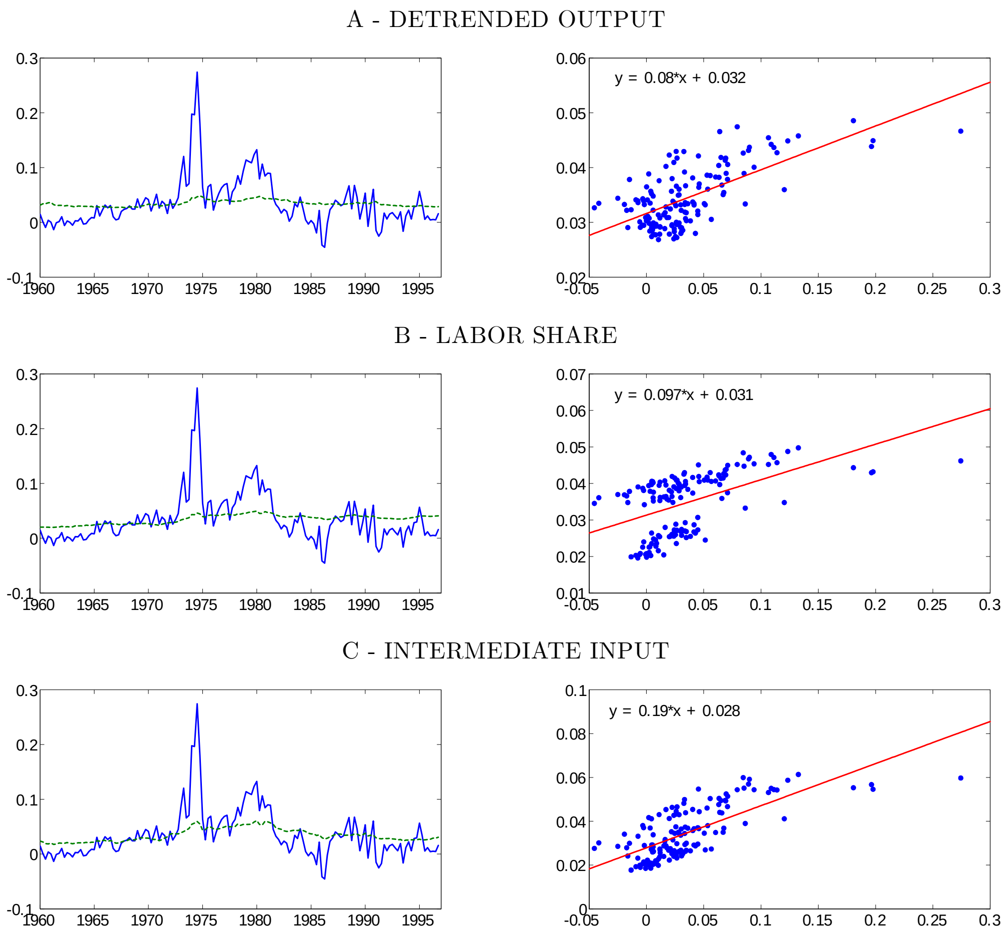

FIGURE 2. Actual and predicted inflation from the purely forward-looking NKPC. The left-hand panel reports actual inflation (solid line) against predicted inflation (dashed line). The right-hand panel displays the scatter plot and the estimated coefficients from the linear regression.

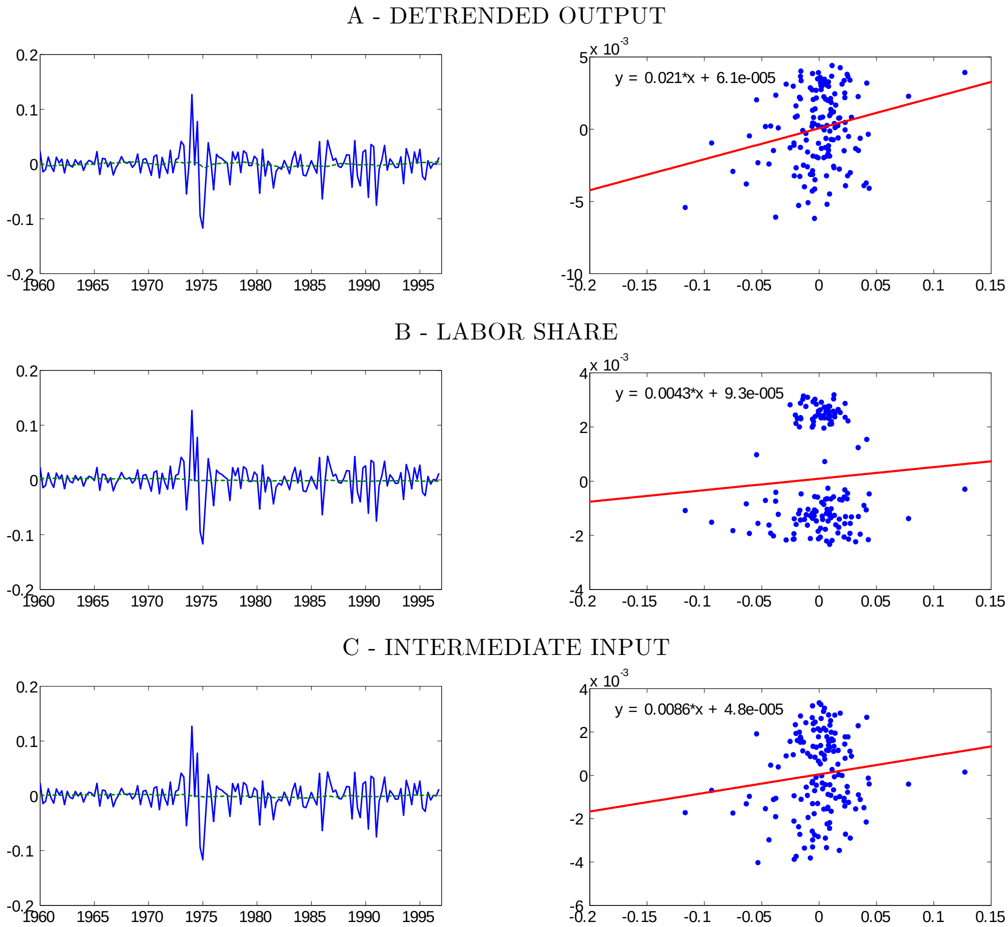

FIGURE 3. Fit of the hybrid model for $\varphi \leq 0.5$. The left-hand panel reports the change in actual inflation (solid line) against the predicted change in inflation (dashed line). The right-hand panel displays the scatter plot and the estimated coefficients from the linear regression.

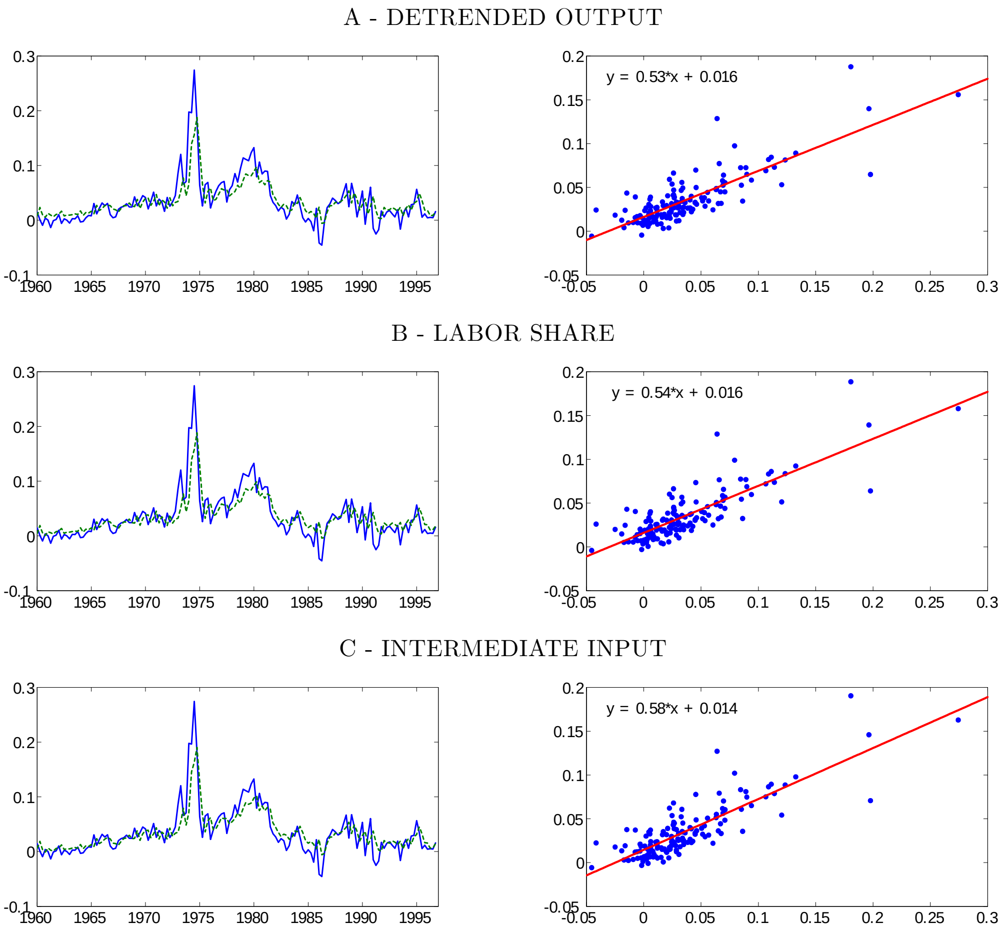

FIGURE 4. Fit of the hybrid model for $\varphi > 0.5$. The left-hand panel reports actual inflation (solid line) against predicted inflation (dashed line). The right-hand panel displays the scatter plot and the estimated coefficients from the linear regression.

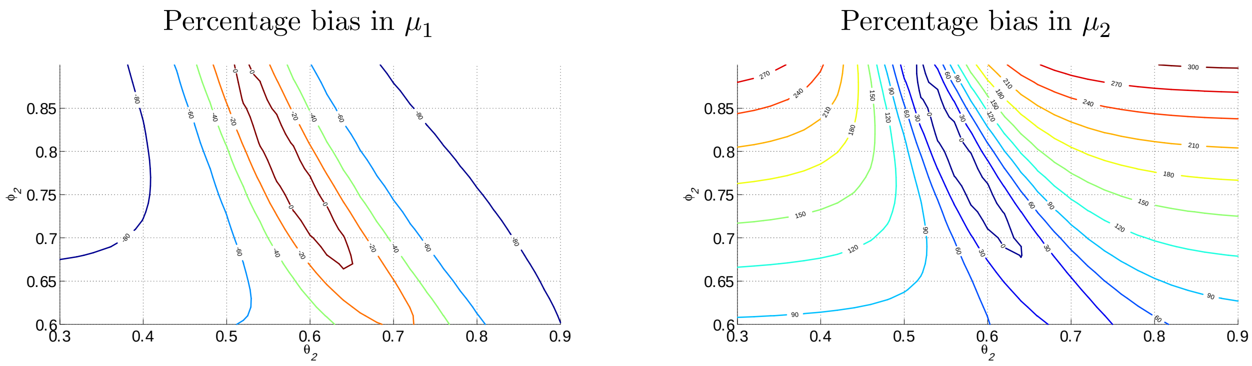

FIGURE 5. Bias in the GMM estimates of μ_1 and μ_2, for different values of φ_2 and θ_2. For each parameter the bias is computed as the percentage deviation of the estimated parameter from the true value, i.e. $BIAS_{\mu_i}= 100\times\left[\left(\hat{\mu}_i-\mu_i\right)/\mu_i\right]$, where $\hat{\mu}_i$ stands for the estimated parameter, while μ_i denotes the true value.

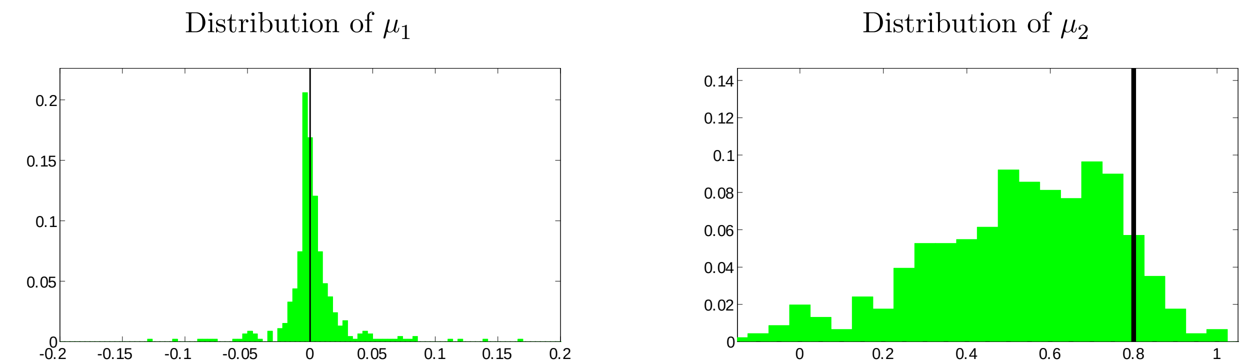

FIGURE 6. Empirical bias in the estimates of μ_1 and μ_2. The light area corresponds to the histogram of the estimated NKPC parameters at the sectoral level (under $\varphi > 0.5$ and with the income share of intermediate goods as a proxy for the forcing variable). The black line corresponds to the estimated coefficients in the "aggregate" regression.

Appendix A: Interpolation of the Data

The empirical performance of the NKPC has generally been evaluated with quarterly data. To enhance the comparison with past evidence we convert the original yearly data to a quarterly frequency. In this appendix we review the methodology used to interpolate the data of the NBER-CES Manufacturing Industry Database.

The estimation of the unobserved quarterly movements in the annual data is accomplished through the methodology developed by Fernandez (1981), which generalizes the method set out by Chow and Lin (1971) by allowing for non-stationary errors in the linear stochastic relationship generating the missing observations. For a given annual observation of a variable we estimate quarterly values so that the within year average of the quarterly series is equal to the observed annual value. Denoting the original $T \times 1$ vector of annual observations by $\mathbf{X}_i^a$, the corresponding $4T \times 1$ quarterly series $\mathbf{X}_i^q$ can be written as

$$\mathbf{X}_i^a = \mathbf{A}'\mathbf{X}_i^q,$$

$$\mathbf{A} = \frac{1}{4}\begin{bmatrix} \mathbf{1}_{1\times 4} & \mathbf{0}_{1\times 4} & \cdots & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{1\times 4} & \mathbf{1}_{1\times 4} & & \vdots \\ \vdots & & \ddots & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{1\times 4} & \cdots & \mathbf{0}_{1\times 4} & \mathbf{1}_{1\times 4} \end{bmatrix}',$$

where $\mathbf{A}$ is a $4T \times T$ matrix and $\mathbf{1}_{1\times 4}$ and $\mathbf{0}_{1\times 4}$ are 1×4 row vectors of ones and zeros respectively. Furthermore, we assume that the unobserved quarterly series follow a linear stochastic relationship with a set of k related observed quarterly series. The error term follows a random walk. Setting up the problem in terms of a multiple regression model, it is assumed that the quarterly series satisfy the relationship

$$\begin{aligned} \mathbf{X}^q &= \mathbf{FB} + \mathbf{e}, \\ \mathbf{De} &= \mathbf{u}, \end{aligned}$$

where $\mathbf{X}^q$ is a $4T \times I$ matrix with quarterly interpolated series, $\mathbf{X}^q = \left[\mathbf{X}_1^q, ..., \mathbf{X}_I^q\right]$, $\mathbf{F}$ is the $4T \times k$ matrix of the observed quarterly series, with $\mathbf{B}$ being the associated loadings and the $4T \times 4T$ first difference transformation matrix $\mathbf{D}$ can be written as

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & \cdots & & 0 \\ -1 & 1 & 0 & & \vdots \\ 0 & \ddots & \ddots & \ddots & \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 1 \end{bmatrix}.$$

Assuming that $u_{i0} = 0$ and constant variance $Var\left(u_{i1}\right) = \sigma_i^2$, $\forall i$, the residuals of the model in first difference

$$\mathbf{DX}^q = \mathbf{DFB} + \mathbf{De}$$

have the usual classical properties. Therefore, the interpolation with this method is BLUE (Fernandez, 1981). The optimal linear unbiased estimator for the unobserved quarterly data, $\mathbf{X}^q$, is given by

$$\begin{aligned} \widehat{\mathbf{X}}^q &= \mathbf{F}\widehat{\mathbf{B}} + \left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{A}\left(\mathbf{A}'\left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{A}\right)^{-1}\left[\mathbf{X}^a - \mathbf{A}'\mathbf{F}\widehat{\mathbf{B}}\right], \\ \widehat{\mathbf{B}} &= \left[\mathbf{F}'\mathbf{A}\left(\mathbf{A}'\left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{A}\right)^{-1}\mathbf{A}'\mathbf{F}\right]^{-1}\mathbf{F}'\mathbf{A}\left(\mathbf{A}'\left(\mathbf{D}'\mathbf{D}\right)^{-1}\mathbf{A}\right)^{-1}\mathbf{X}^a. \end{aligned}$$

We have outlined the standard case where an appropriate set of observable quarterly series to be used in the interpolation exists. The next issue which needs to be confronted when applying the estimator above pertains to the choice of the appropriate k quarterly related regressors, which make up the columns of $\mathbf{F}$. Since there is not an appropriate match for each of the observable series and the industry data at the SIC 4-digit level, we make use of an extended information set in an effort to maximize the fit with our annual NBER measures. For each series we construct a large dataset of disaggregate and aggregate variables which are believed to have valuable information for the interpolation. For example, to interpolate the price indexes we construct a dataset with 71 series with aggregate and disaggregate prices at the product level, collected from the FRED and the Bureau of Labor Statistic (BLS) databases.[39] Stock and Watson (2002) show that the principal components consistently recover the space spanned by the factors when the dimension of the dataset is large and the number of principal components used is at least as large as the true number of factors. Therefore, in the first stage we extract k principal components for each of the large information sets. Given that the original series are nonstationary, the factor are estimated following the procedure outlined in Bai (2004).[40] The decision rule we employ with respect to how many principle components to retain is the IC_1 criteria of Bai (2004), with a maximum of 10 factors allowed in each case.[41] We then use these factors as the set of regressors for the interpolation, in the procedure outlined above. Note that this two-step approach implies the presence of "generated regressors" in the second step.

The obvious advantage of having access to such a large set of related regressors for each variable is that the estimated factors will also capture the cross industry correlations arising from the underlying complementarities and substitutabilities in production (see also Leith and Malley, 2007). However, sectoral idiosyncrasy is preserved and given by the error term in the interpolation regressions as well as the idiosyncratic loadings on the common factors. In principle, this methodology should preserve the cross-sectional dependence as well as the time series properties of the original data.

[39]The dataset for the average hourly earning includes 31 series from the BLS; that for the numbers of workers includes 53 disaggregated series; that for hours 34. The dataset for industry output includes 207 disaggregated series for industrial production.

[40]Notice that the dataset from which we extract the factors is largely unbalanced. In order to estimate the factors we follow procedure outlied by Stock and Watson (2002, Appendix A) and fill in the dataset recursively with an EM algorithm that makes use of the factor structure of the dataset. This imputation strategy requires that the missing data can be considered missing at random (MRA), see Rubin (1976). This condition is easily satisfied in our case.

[41]We obtain similar results if we extract factors following the procedure indicated by Bai and Ng (2004).

Appendix B: Results at the 2-digit Sectoral Level

TABLE B1

	Output Gap		Labor Share		Input Share		# of Sectors
	γ	fit	γ	fit	γ	fit	
All	-0.0068***	0.0672	-0.0052***	0.0485	0.0063***	0.0716	
	(0.0015)	0.6648	(0.0008)	0.5180	(0.0020)	0.7283	
	63		47		174		458
SIC 20	-0.0292***	0.0665	-0.0122**	0.0634	0.0024	0.0543	
	(0.0111)	0.4518	(0.0048)	0.4030	(0.0103)	0.5070	
	3		7		10		49
SIC 21	0.0108*	0.0321	-0.0062**	0.0247	-0.0021	0.0480	
	(0.0065)	0.1697	(0.0027)	0.2215	(0.0016)	0.0271	
	0		2		1		4
SIC 22	-0.0021	0.0521	0.0031	0.0416	0.0157*	0.0437	
	(0.0027)	0.3531	(0.0049)	0.4599	(0.0081)	0.3862	
	1		3		4		23
SIC 23	-0.0036	0.0843	-0.0004	0.0415	-0.0099***	0.0458	
	(0.0025)	0.5598	(0.0022)	0.4777	(0.0037)	0.5443	
	6		8		6		31
SIC 24	0.0117	0.0199	-0.0265***	0.0343	0.0048	0.0292	
	(0.0086)	0.0715	(0.0086)	0.2014	(0.0168)	0.2067	
	0		4		6		17
SIC 25	-0.0021	0.0734	-0.0066***	0.0244	-0.0088	0.0564	
	(0.0027)	0.5881	(0.0022)	0.5015	(0.0102)	0.5715	
	0		2		3		13
SIC 26	0.0041	0.0531	-0.0071**	0.0622	-0.000	0.0801	
	(0.0059)	0.3427	(0.0028)	0.3081	(0.0062)	0.6024	
	1		3		2		17
SIC 27	0.0033	0.0180	-0.0044***	0.0367	0.0015	0.0277	
	(0.0051)	0.1976	(0.0010)	0.3068	(0.0041)	0.4343	
	1		2		2		14
SIC 28	-0.0158***	0.1064	-0.0022	0.0741	0.0081*	0.0993	
	(0.0055)	0.5365	(0.0022)	0.4304	(0.0043)	0.5579	
	4		4		7		29
SIC 29	0.0096	0.0733	-0.0052	0.0272	0.0500***	0.1109	
	(0.0191)	0.1467	(0.0031)	0.1671	(0.0194)	0.2937	
	1		1		2		5

	Output Gap		Labor Share		Input Share		# of Sectors
	γ	fit	γ	fit	γ	fit	
SIC 30	-0.0173***	0.1263	-0.0015	0.0638	0.0138*	0.0831	
	(0.0022)	0.5557	(0.0022)	0.4181	(0.0078)	0.3893	
	2		1		5		15
SIC 31	-0.0031	0.0221	0.0010	0.0213	0.0081	0.0468	
	(0.0050)	0.2462	(0.0045)	0.3198	(0.0071)	0.3525	
	1		2		5		11
SIC 32	-0.0075*	0.0551	-0.0069***	0.0418	0.0078**	0.0709	
	(0.0043)	0.5483	(0.0013)	0.4584	(0.0030)	0.5215	
	5		5		7		25
SIC 33	-0.0027	0.0507	-0.0085	0.0561	0.0144	0.0951	
	(0.0040)	0.3107	(0.0058)	0.6774	(0.0162)	0.5984	
	1		2		8		26
SIC 34	-0.0081***	0.0537	-0.0050***	0.0634	0.0148***	0.0772	
	(0.0023)	0.5533	(0.0018)	0.5205	(0.0058)	0.6950	
	8		6		9		38
SIC 35	-0.0047***	0.0731	-0.0016*	0.0381	0.0081**	0.0808	
	(0.0013)	0.6837	(0.0009)	0.3070	(0.0038)	0.6357	
	8		8		9		51
SIC 36	-0.0115***	0.1083	-0.0043***	0.0404	0.0003	0.0843	
	(0.0022)	0.5874	(0.0013)	0.3740	(0.0048)	0.7652	
	9		10		14		37
SIC 37	-0.0035	0.0665	-0.0053	0.0330	0.0064	0.0949	
	(0.0033)	0.6197	(0.0019)	0.3114	(0.0049)	0.5905	
	3		3		5		18
SIC 38	0.0027	0.0348	-0.0010***	0.0408	-0.0049	0.1128	
	(0.0033)	0.3649	(0.0013)	0.5041	(0.0044)	0.5963	
	1		4		3		17
SIC 39	0.0046	0.0707	-0.0039*	0.0665	0.0200***	0.0730	
	(0.0030)	0.5408	(0.0018)	0.3141	(0.0086)	0.5646	
	1		3		6		18

Notes: Table B1 reports a summary of the estimates of the closed-form solution to the purely forward-looking NKPC. We report the mean group estimate of γ and the associated standard error (in parenthesis) calculated through the non-parametric estimator proposed by Pesaran and Smith (1995); ***/**/* denotes significant at 1/5/10 percent level, respectively. The measures reported in the fit column are the average R^2 and the correlation between predicted and realized aggregate inflation. The entry below the estimates is the number of SIC 4-digit sectors for which coefficient estimates are positive and significant at the 10% level. The last column reports the number of 4-digit sectors in the broadly defined class reported on the left-hand side. The sample period is 1958:Q1 to 1996:Q4.

TABLE B2

	Output Gap			Labor Share			Input Share			# of Sectors
	λ_1	λ_2	fit	λ_1	λ_2	fit	λ_1	λ_2	fit	
All	0.0293^{***}	0.1944^{***}	0.0123	0.0200^{***}	0.1228^{***}	0.0030	0.0130^{*}	0.1286^{***}	0.0039	
	(0.0035)	(0.0337)	0.2234	(0.0030)	(0.0335)	0.0616	(0.0071)	(0.0333)	0.1256	
	67			44			39			458
SIC 20	0.0735^{***}	0.1352	0.0138	0.0661^{***}	0.2997^{***}	0.0056	0.0219	0.3605^{***}	0.0038	
	(0.0161)	(0.1113)	0.1285	(0.0180)	(0.0950)	0.0318	(0.0368)	(0.0960)	0.0465	
	5			8			4			49
SIC 21	0.1725	-0.0476	0.0043	0.0240^{**}	-0.2961	0.0019	0.0036	0.2844	0.0010	
	(0.1827)	(0.4594)	0.0971	(0.0101)	(0.2452)	0.0300	(0.0058)	(0.3338)	0.0285	
	0			0			0			4
SIC 22	0.0066^{***}	0.5336^{***}	0.0085	0.0312^{**}	0.3654^{**}	0.0024	0.0048	0.3381^{**}	0.0038	
	(0.0047)	(0.1209)	0.1214	(0.0139)	(0.1476)	0.0847	(0.0218)	(0.1439)	0.1226	
	3			5			3			23
SIC 23	0.0131	0.4138^{***}	0.0067	0.0031	0.3748^{***}	0.0036	0.0401^{***}	-0.0491	0.0024	
	(0.0046)	(0.1145)	0.1393	(0.0060)	(0.1181)	0.0798	(0.0138)	(0.1444)	0.1186	
	6			4			3			31
SIC 24	0.0411^{***}	0.4395^{**}	0.0042	-0.0024	-0.2027	0.0039	-0.0212	0.3788^{**}	0.0048	
	(0.0287)	(0.1802)	0.0735	(0.0267)	(0.1849)	0.0773	(0.0231)	(0.1686)	0.1000	
	7			2			0			17
SIC 25	0.0179^{**}	0.2520^{**}	0.0114	0.0060^{***}	0.7478^{***}	0.0027	0.0284^{**}	-0.0638	0.0020	
	(0.0066)	(0.1239)	0.1844	(0.0017)	(0.0366)	0.0685	(0.0139)	(0.1933)	0.0527	
	0			2			1			13
SIC 26	0.0264^{*}	0.3902^{**}	0.0238	0.0134	0.0649	0.0050	0.0182	0.3620^{**}	0.0061	
	(0.0111)	(0.1689)	0.2836	(0.0100)	(0.1755)	0.0903	(0.0128)	(0.1825)	0.1940	
	2			1			3			17
SIC 27	0.0178^{*}	0.1248	0.0075	0.0085	-0.0960	0.0011	0.0097	-0.0117	0.0013	
	(0.0107)	(0.1747)	0.0880	(0.0058)	(0.2007)	0.0350	(0.0134)	(0.2077)	0.0213	
	0			0			1			14
SIC 28	0.0380^{***}	0.0859	0.0247	0.0043	-0.1068	0.0028	0.0200	0.0682	0.0034	
	(0.0142)	(0.1386)	0.2835	(0.0060)	(0.1237)	0.0727	(0.0191)	(0.1368)	0.1048	
	3			0			2			29
SIC 29	0.0341^{**}	0.6762^{***}	0.0143	0.0144	-0.0246	0.0011	0.0166^{**}	0.8647^{***}	0.0041	
	(0.0144)	(0.1855)	0.0462	(0.0132)	(0.3931)	0.0329	(0.0078)	(0.0481)	0.0757	
	1			0			2			5

	Output Gap			Labor Share			Input Share			# of Sectors
	λ_1	λ_2	fit	λ_1	λ_2	fit	λ_1	λ_2	fit	
SIC 30	0.0349***	0.0216	0.0356	0.0144	-0.0543	0.0039	-0.0436***	-0.3053*	0.0071	
	(0.0078)	(0.1662)	0.2582	(0.0115)	(0.2047)	0.0859	(0.0161)	(0.1804)	0.1218	
	2			3			0			15
SIC 31	0.0457**	0.2365	0.0040	0.0179	-0.0798	0.0007	-0.0065	0.1045	0.0041	
	(0.0209)	(0.2212)	0.0851	(0.0129)	(0.2791)	0.0362	(0.0160)	(0.2318)	0.1050	
	0			1			1			11
SIC 32	0.0158**	0.0855	0.0074	0.0100	0.2127	0.0028	0.0145	-0.0101	0.0029	
	(0.0062)	(0.1606)	0.0987	(0.0079)	(0.1489)	0.0674	(0.0117)	(0.1356)	0.1466	
	6			2			3			25
SIC 33	0.0628**	0.2616*	0.0148	0.0615***	0.1267	0.0038	0.0780	0.0827	0.0092	
	(0.0260)	(0.1381)	0.1857	(0.0201)	(0.1324)	0.0444	(0.0786)	(0.1365)	0.1946	
	4			3			0			26
SIC 34	0.0124**	0.2829**	0.0152	0.0131***	0.1789	0.0032	-0.0484	0.0428	0.0063	
	(0.0063)	(0.1151)	0.2309	(0.0041)	(0.1150)	0.1139	(0.0308)	(0.1209)	0.2530	
	10			6			2			38
SIC 35	0.0126***	0.1426	0.0076	0.0163***	0.0511	0.0023	0.0034	0.1938**	0.0023	
	(0.0040)	(0.1035)	0.1936	(0.0049)	(0.0922)	0.0628	(0.0100)	(0.0933)	0.0893	
	3			1			4			51
SIC 36	0.0234***	-0.0109	0.0141	0.0094	-0.0487	0.0015	0.0165**	0.0315	0.0028	
	(0.0090)	(0.1220)	0.2090	(0.0058)	(0.1278)	0.0541	(0.0073)	(0.1065)	0.1525	
	6			4			2			37
SIC 37	0.0083***	0.1024	0.0029	0.0050	0.0816	0.0022	0.0215*	0.0171	0.0014	
	(0.0026)	(0.1844)	0.1079	(0.0031)	(0.1781)	0.0610	(0.0123)	(0.1581)	0.0429	
	6			0			2			18
SIC 38	0.0092	0.0096	0.0065	0.0196***	0.1021	0.0012	0.0333**	0.0061	0.0027	
	(0.0071)	(0.1808)	0.2006	(0.0070)	(0.1744)	0.0542	(0.0130)	(0.1885)	0.1174	
	2			1			2			17
SIC 39	0.0189***	0.0565	0.0127	0.0055	0.1215	0.0024	0.0454*	0.2423	0.0054	
	(0.0061)	(0.1847)	0.1676	(0.0080)	(0.1635)	0.0623	(0.0235)	(0.1591)	0.1237	
	1			1			4			18

Notes: Table B2 reports a summary of the estimates of the closed-form solution to the hybrid NKPC, with $\varphi \leq 0.5$. We report the mean group estimate of γ and the associated standard error (in parenthesis) calculated through the non-parametric estimator proposed by Pesaran and Smith (1995); $^{***}/^{**}/^{*}$ denotes significant at 1/5/10 percent level, respectively. The measures reported in the fit column are the average R^2 and the correlation between predicted and realized aggregate inflation. The entry below the estimates is the number of SIC 4-digit sectors for which coefficient estimates are positive and significant at the 10% level. The last column reports the number of 4-digit sectors in the broadly defined class reported on the left-hand side. The sample period is 1958:Q1 to 1996:Q4.

TABLE B3

	Output Gap			Labor Share			Input Share			# of Sectors
	μ_1	μ_2	fit	μ_1	μ_2	fit	μ_1	μ_2	fit	
All	-0.0050	0.5470***	0.0086	-0.0010	0.5753***	0.0068	0.0038***	0.5502***	0.0117	
	0.0032	0.0114	0.8223	0.0007	0.0106	0.8191	0.0014	0.0109	0.8368	
	74	422		34	438		141	436		458
SIC 20	-0.0451*	0.3985***	0.0147	-0.0023	0.4806***	0.0142	-0.0012	0.4961***	0.0130	
	0.0278	0.0368	0.4489	0.0030	0.0321	0.4539	0.0089	0.0353	0.4925	
	3	39		5	47		6	46		49
SIC 21	0.0069	0.3665***	0.0060	-0.0002	0.2475***	0.0204	0.0004	0.4148***	0.0164	
	0.0045	0.2401	0.4587	0.0047	0.2494	0.4614	0.0013	0.2238	0.4553	
	0	4		1	3		1	3		4
SIC 22	0.0020	0.4893***	0.0074	0.0018	0.5559***	0.0065	0.0106	0.5111***	0.0088	
	0.0022	0.0382	0.6155	0.0023	0.0321	0.6158	0.0076	0.0415	0.6181	
	6	22		6	23		7	21		23
SIC 23	-0.0006	0.5044***	0.0145	0.0008	0.5546***	0.0065	-0.0020	0.5134***	0.0113	
	0.0013	0.0457	0.6935	0.0015	0.0295	0.6805	0.0026	0.0359	0.6870	
	4	27		6	31		5	29		31
SIC 24	0.0091**	0.4294***	0.0066	-0.0119**	0.4618***	0.0125	0.0010	0.4409***	0.0076	
	0.0047	0.0512	0.4546	0.0047	0.0327	0.4653	0.0086	0.0399	0.4628	
	7	15		0	17		6	17		17
SIC 25	0.0018	0.5097***	0.0087	-0.0043***	0.4677***	0.0063	0.0067	0.4703***	0.0087	
	0.0021	0.0722	0.6580	0.0014	0.0849	0.6511	0.0075	0.0600	0.6625	
	4	12		0	11		4	12		13
SIC 26	0.0079	0.7280***	0.0036	-0.0001	0.8057***	0.0055	-0.0031	0.7093***	0.0115	
	0.0051	0.0490	0.7370	0.0006	0.0385	0.7378	0.0034	0.0540	0.7501	
	3	17		0	17		2	16		17
SIC 27	0.0037	0.4936***	0.0041	-0.0031***	0.4231***	0.0090	0.0028	0.4535***	0.0066	
	0.0032	0.0795	0.5817	0.0009	0.0862	0.5999	0.0026	0.0849	0.5819	
	3	14		0	12		6	11		14
SIC 28	-0.0018	0.5877***	0.0114	0.0024	0.6559***	0.0093	0.0033**	0.6390***	0.0165	
	0.0041	0.0510	0.8447	0.0027	0.0327	0.8409	0.0016	0.0441	0.8491	
	5	26		3	28		8	28		29
SIC 29	-0.0194	0.7227***	0.0078	-0.0021	0.6615***	0.0052	0.0310	0.6917***	0.0171	
	0.0204	0.0195	0.3752	0.0020	0.0547	0.3815	0.0209	0.1254	0.4164	
	1	5		0	5		4	5		5

	Output Gap			Labor Share			Input Share			# of Sectors
	μ_1	μ_2	fit	μ_1	μ_2	fit	μ_1	μ_2	fit	
SIC 30	-0.0061**	0.5338***	0.0037	-0.0007	0.6883***	0.0017	0.0062**	0.6660***	0.0046	
	0.0025	0.0555	0.8644	0.0010	0.0467	0.8639	0.0031	0.0422	0.8647	
	0	14		1	15		8	15		15
SIC 31	-0.0322	0.4521***	0.0060	0.0052	0.4991***	0.0078	0.0083*	0.4587***	0.0116	
	0.0304	0.0663	0.4781	0.0067	0.0533	0.4708	0.0055	0.0404	0.4770	
	1	10		1	11		3	11		11
SIC 32	-0.0027	0.5306***	0.0068	-0.0034***	0.5939***	0.0021	0.0037*	0.5291***	0.0105	
	0.0024	0.0471	0.7445	0.0006	0.0335	0.7358	0.0024	0.0632	0.7480	
	4	24		0	25		10	24		25
SIC 33	0.0032	0.6854***	0.0067	0.0021	0.6687***	0.0051	0.0106	0.6117***	0.0153	
	0.0042	0.0256	0.7944	0.0049	0.0406	0.7986	0.0101	0.0321	0.8077	
	6	26		2	24		9	26		26
SIC 34	0.0002	0.6515***	0.0044	0.0006	0.6474***	0.0042	0.0070*	0.6408***	0.0083	
	0.0019	0.0362	0.8368	0.0056	0.0286	0.8385	0.0041	0.0269	0.8414	
	6	36		3	36		13	38		38
SIC 35	-0.0002	0.5976***	0.0086	-0.0021***	0.6123***	0.0072	0.0024	0.5125***	0.0124	
	0.0014	0.0313	0.7708	0.0005	0.0319	0.7712	0.0016	0.0318	0.7791	
	4	47		1	47		19	50		51
SIC 36	-0.0009	0.5555***	0.0111	-0.0015***	0.5649***	0.0033	0.0014	0.5915***	0.0104	
	0.0012	0.0386	0.8393	0.0004	0.0430	0.8325	0.0019	0.0357	0.8531	
	4	33		1	36		12	36		37
SIC 37	-0.0017	0.5924***	0.0092	-0.0011***	0.6024***	0.0032	0.0052	0.5602***	0.0146	
	0.0015	0.0419	0.7201	0.0004	0.0407	0.7095	0.0033	0.0569	0.7368	
	2	18		1	17		7	16		18
SIC 38	0.0030	0.5005***	0.0046	-0.0005	0.5505***	0.0018	-0.0009	0.4630***	0.0212	
	0.0030	0.0445	0.7672	0.0007	0.0383	0.7658	0.0028	0.0548	0.7888	
	4	17		2	17		4	16		17
SIC 39	0.0051*	0.5414***	0.0072	-0.0017	0.4497***	0.0068	0.0114*	0.5462***	0.0103	
	0.0028	0.0636	0.7803	0.0014	0.0687	0.7749	0.0071	0.0602	0.7813	
	7	16		1	16		7	16		18

Notes: Table B3 reports a summary of the estimates of the closed-form solution to the hybrid NKPC, with $\varphi > 0.5$. We report the mean group estimate of γ and the associated standard error (in parenthesis) calculated through the non-parametric estimator proposed by Pesaran and Smith (1995); $^{***}/^{**}/^{*}$ denotes significant at 1/5/10 percent level, respectively. The measures reported in the fit column are the average partial R^2 for $\mu_1$at and the correlation between predicted and realized aggregate inflation. The entry below the estimates is the number of SIC 4-digit sectors for which coefficient estimates are positive and significant at the 10% level. The last column reports the number of 4-digit sectors in the broadly defined class reported on the left-hand side. The sample period is 1958:Q1 to 1996:Q4.