Evaluating the German (New Keynesian) Phillips Curve

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This version: May 2008

Abstract

This paper evaluates the New Keynesian Phillips Curve (NKPC) and its hybrid variant within a limited information framework for Germany. Our main interest rests on the average frequency of price re-optimization of firms, which can be estimated by nonlinear regression techniques. Therefore, we use the labor income share as the driving variable and conduct a GMM estimation strategy as proposed by Galí and Gertler (1999) and Galí, Gertler and López-Salido (2001). We also consider a source of real rigidity by allowing for a fixed firm-specific capital stock. Furthermore, we expand the basic empirical framework by several tests to check the robustness of the NKPC specification. This also includes a procedure that is robust to weak instruments. We find out that the German Phillips Curve is purely forward looking. Moreover, our point estimates are consistent with the view that firms re-optimize prices every two quarters. While these estimates seem plausible from an economic point of view, the uncertainty around these estimates are very large and also consistent with perfect nominal price rigidity where firms never re-optimize their prices. In contrast to previous studies, we do no detect problems with weak identification, but we do find some evidence that the model might be misspecified.

JEL-Classification: E31, C13, C52
Keywords: Inflation dynamics, Phillips Curve, Weak instruments, Optimal instruments

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1 Introduction

Explaining the evolution of aggregate prices is one of the most prominent issues in empirical macroeconomics. Nowadays, the canonical inflation model is the New Keynesian Phillips Curve (NKPC). Similar to earlier Phillips Curve specifications the NKPC relates price behavior to a measure of real economic activity. But, in contrast to traditional ones the NKPC can be derived directly from optimizing behavior of households and firms and thus builds on a suitable micro-foundation. The NKPC framework assumes monopolistically competitive firms that face nominal prices rigidities. The standard model of staggered price adjustment Calvo (1983) has the attractive property that the coefficients of the NKPC directly depend on the average frequency with which prices are adjusted in the economy.

The aim of this paper is to determine the degree of nominal price rigidity in the German economy. Therefore we estimate the NKPC and allow for different specifications. A generalized version of the model proposed by Christiano, Eichenbaum and Evans (2005) is employed as our benchmark model specification that assumes a dynamic indexation scheme for those firms that do not re-optimize. Furthermore, we also consider a model with "rule-of-thumb" firms in the spirit of Galí and Gertler (1999) and Galí et al. (2001). We follow Galí et al. (2001) and Sbordone (2002) and allow for some real rigidities through the assumption of firm-specific capital.

Empirical studies that assess the degree of nominal price rigidity in the German economy through estimations of the Phillips curve are still rare. The primary evidence steams from cross country comparisons. Examples are Banerjee and Batini (2004), Leith and Malley (2007) or Rumler (2007). This evidence is in most cases based upon GMM estimation with additional aspects of an open economy. While the open economy aspect seems to be unimportant for Germany (at least according to Banerjee and Batini, 2004; Leith and Malley, 2007), their results vary considerably with respect to the degree of nominal price rigidity. The estimated average frequency of price re-optimization ranges form 2.5 quarters (Banerjee and Batini, 2004) to 13 quarters (Leith and Malley, 2007). Additionally, there is also disagreement on whether the inflation contains a lagged term (through backward looking behavior) or whether it is purely forward looking. A more rigorous treatment of nominal price rigidity in Germany is provided by Coenen, Levin and Christoffel (2007) that focuses on the interaction of real and nominal rigidities. Their estimation technique relies on indirect inference methods. Their results are based on a generalized Calvo model and find a frequency of price reoptimization of roughly two quarters.

Our empirical strategy is as follows. We apply a standard GMM method to estimate the structural parameters of the Phillips Curve. Special attention is payed to the selection of relevant instruments. We then evaluate the robustness of our results with respect to several parameter restrictions, measures of real rigidity and additional lags of inflation. Next, we conduct an identification robust procedure based on a nonlinear Anderson-Rubin (AR) statistic (where we follow Ma, 2002; Mavroeidis, 2006) and compare this results with those obtained from standard GMM estimation. As long as there are weak instrument problems present, the two procedures should display quite different results.

For a given reasonable degree of real rigidity, the estimates of the frequency of price re-optimization point to about 2.5 quarters. But this estimate is surrounded by a large degree of uncertainty, since the confidence intervals for this estimate are very large. Unless we do not restrict other parameter values, the estimated degree of nominal rigidity is both consistent with a very low degree of price stickiness and with a situation where prices are never re-optimized (perfect price rigidity). This also casts doubt concerning the proxy of marginal cost, the labor share, as driving variable of inflation (a finding that is also obtained by Mavroeidis, 2006, for the US). Moreover, we find that backward looking behavior is unimportant for explaining the German inflation process and thus find that a purely forward looking specification is more appropriate. The identification robust procedure does not indicate serve problems of weak instruments. However there is some evidence of misspecification of the model (but not detected by the conventional J statistic).

This paper is organized as follows. We first present our basic model framework in Section 2. Then we turn to the econometric strategy for estimating and testing the different model specifications (Section 3). In section 4 we discuss our data set and how we obtain the instrument set. Next, we present our econometric results (Section 5). In Section 6 we test for an augmented inflation model. Then, we compare the GMM results with an identification robust procedure (Section 7). Finally, we draw some conclusions in Section 8.

2 The Modeling Framework

This section presents the basic theoretical framework that includes monopolistically competitive goods markets and price stickiness. These are the two key elements in modern macroeconomic models that are used to analyze monetary policy. This model structure tries to ensure that it is consistent with the behavior of optimizing economic agents. Here, we are mainly interested in the price setting behavior of firms in order to derive an expression for aggregate inflation. Therefore, we assume random price contracts due to Calvo (1983) that is now standard in many macroeconomic models (i.e. Smets and Wouters, 2003; Christiano et al., 2005). However, we deviate form the standard Calvo model and assume that capital is firm-specific and is subject to a form of real rigidity, so that capital cannot be instantaneously reallocated and is thus a predetermined factor.[1]

2.1 The Market Structure

As standard in New Keynesian models, we assume a monopolistic competitive environment with a continuum of firms indexed by $i \in [0,1]$. Each firm i produces a differentiated good $Y_t(i)$ according to a Cobb-Douglas technology

$$Y_t(i) = A_t \overline{K}_t(i)^{\alpha} N_t(i)^{1-\alpha}, \tag{1}$$

where A_t is a common country wide technological factor, $\overline{K}_t(i)$ is the (fixed) firm-specific capital stock and $N_t(i)$ is the labor factor employed by firm i.

Each firm i is faced with a demand function with a constant elasticity of substitution that is given by

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} Y_t, \tag{2}$$

where Y_t is aggregate output (which equals aggregate demand), P_t is the aggregate price level in the economy and $P_t(i)$ is the price that firm i charges for good $Y_t(i)$. The price elasticity of demand for good i is equal to ϵ (with $\epsilon > 0$).[2]

[1] Here we follow Galí et al. (2001) and Sbordone (2002). See also Eichenbaum and Fisher (2007) for a more rigorous treatment of real rigidities in the Calvo price setting framework

[2] According to Dixit and Stiglitz (1977) aggregate output Y_t is a constant-elasticity-of-

Without any price frictions the price of the differentiated good is set as a constant mark-up over nominal marginal costs

$$P_t(i) = \mu \frac{W_t}{(1-\alpha)Y_t(i)/N_t(i)} = \mu MC_t(i), \tag{3}$$

with $\mu = \epsilon/(\epsilon - 1)$. In a symmetric equilibrium, all firms produce the same output, employ the same labor inputs and charge the same price. In this situation $p_t(i) = p_t$ (expressed in logs) and the optimal price under perfect price flexibility is equal to $p_t = \log(\mu) + mc_t$.

2.2 The Calvo Model

The second essential element of New Keynesian Macroeconomics are nominal rigidities. Sticky price models are now frequently employed to study the monetary transmission process. In the following analysis we concentrate solely on time-dependent models where we use in particular a Calvo (1983) style model.[3] This framework assumes that each firm optimizes its prices only from time to time. This is motivated by costs associated with information gathering. The frequency of price reoptimization is thus a stochastic process with a constant probability that a firm sets its prices in an optimal way at each point in time. So, there is always a fraction of firms $1 - \theta$ in the economy that optimally adjust its prices. The expected waiting time between these price changes is given by $1/(1 - \theta)$.

substitution aggregator $Y_t = \left[\int_0^1 Y_t(i)^{(\epsilon-1)/\epsilon} di\right]^{\epsilon/(\epsilon-1)}$. This expression abstracts from investment and foreign trade, so output Y_t equals consumption C_t and P_t is the corresponding aggregate price index $P_t = \left[\int_0^1 P_t(i)^{1-\epsilon} di\right]^{1/(1-\epsilon)}$.

[3]Another model class are state-dependent sticky prices models where the number of firms that changes prices in a given period is determined endogenously (i.e. Dotsey, King and Wolman, 1999). Another popular model besides the one of Calvo (1983) was developed by Taylor (1980).

A firm that reoptimizes, sets its price $P_t^*(i)$ in order to maximizes the expected discounted sum of profits

$$E_t \sum_{k=0}^{\infty} (\beta\theta)^k \upsilon_{t,t+k} \left[P_t^*(i) X_{t,t+k} - MC_{t,t+k}(i) \right] \frac{Y_{t+k}(i)}{P_{t+k}}, \tag{4}$$

subject to the demand constraints (2) and

$$X_{t,t+k} = \begin{cases} \prod_{l=0}^{k-1} \overline{\pi}^{1-\xi} \pi_{t+l}^{\xi} & \text{for } k > 0 \\ 1 & \text{for } k = 0. \end{cases} \tag{5}$$

with β a constant discount factor, $\upsilon_{t,t+k} = U^{'}(C_t)/U^{'}(C_{t+k})$ the time-varying portion of the discount factor between t and $t+k$; with $U^{'}(C_t)$ the marginal utility of consumption. $\overline{\pi}$ is the long-run average gross rate of inflation. When a firm does not reoptimize its price, it is assumed that it resets it according to some sort of indexation scheme. Our baseline specification is the partial indexation scheme used in Smets and Wouters's (2003) model and further discussed by Sahuc (2004) with $\xi \in [0,1]$ that measures the degree of indexation to past inflation. This is a further generalization of Christiano et al.'s (2005) dynamic indexation scheme with $\xi = 1$, where prices are reset according to $P_t(i) = \pi_{t-1} P_{t-1}(i)$ during periods where firms do not reoptimize.

After solving the maximization problem in (4) and some further manipulations,[4] an expression for aggregate inflation can be derived of the form

$$\widehat{\pi}_t = \frac{\xi}{1+\beta\xi} \widehat{\pi}_{t-1} + \frac{\beta}{1+\beta\xi} E_t \widehat{\pi}_{t+1} + \frac{(1-\theta\beta)(1-\theta)}{(1-\beta\xi)\theta} A \widehat{s}_t, \tag{6}$$

[4]See i.e. Sahuc (2004) or Walsh (2003, Ch. 5) for a derivation.

where $\widehat{s}_t$ is the percentage deviation of average marginal cost MC_t/P_t from its steady state. This type of equation is often referred to as the new Keynesian Phillips curve.[5] Note that a particular feature of this inflation equation is that it has a sound microeconomic foundation in a sense that it depends on structural parameters that have a direct economic interpretation. With $\xi = 0$ the expression reduces to the pure forward looking Phillips curve that coincides with a static indexation scheme.[6]

The parameter A measures the degree to which inflation responds to changes in current and future values of real marginal costs. In contrast to a situation where all firms face the same marginal cost ($A = 1$), firm specific marginal cost may differ across firms due to differences in the output level. The differences in the output level are generated through the assumption of a fixed stock of firm-specific capital.[7] As shown by Sbordone (2002) and Galí et al. (2001) A also depends on structural parameters with

$$A = \frac{1-\alpha}{1+\alpha(\epsilon-1)}$$

with ϵ the elasticity of substitution among diffent goods from eq(2) and α the technology parameter form the Cobb-Douglas production function eq(1), whereas $\epsilon > 1$ and $0 < \alpha < 1$.

An additional way of modeling a smaller responds of prices to marginal cost

[5]This expression is an augmented version of a specific relation that does not include the lagged inflation term. This version with an additional inflation lag is sometimes called hybrid Phillips curve.

[6]A static indexation scheme implies that firms set prices according to $P_{it} = \overline{\pi} P_{it-1}$ during periods where they do not reoptimize (i.e. Erceg, Henderson and Levin, 2000).

[7]A more comprehensive discussion for the role of firm-specific capital is given by Eichenbaum and Fisher (2007) firms face convex capital adjustment costs. Our specification of A can be seen as a special case of this framework where the adjustment costs are very high.

is proposed by Eichenbaum and Fisher (2007) and Coenen et al. (2007). They assume a varying elasticity of demand, but as shown by Coenen et al. (2007) this assumption does not lead to a substantial reduction of the sensitivity of prices to marginal cost for reasonable values of α. In order to keep thinks simple we do not consider this type of additional friction.

2.3 A Variant with rule-of-thumb Firms

A variant of the above presented model (6) was presented by Galí and Gertler (1999). In this specification there a two types of firms; one fraction $1-\omega$ that reoptimizes prices according to the model of Calvo (as discussed in sec (2.2)). In periods where firms cannot reoptimize they set prices according to a static indexation scheme. The other fraction ω of non-reoptimizing firms set prices according to a backward looking rule-of-thumb. With probability θ they set $P_{it} = \overline{\pi} P_{it-1}$. Otherwise, with probability $1-\theta$, they apply

$$P_t^{'} = \pi_{t-1}\overline{P}_t$$

with $\overline{P}_t = (1-\omega)P_t^* + \omega P_t^{'}$, where P_t^* is the optimized price that is chosen by the fraction of firms that are forward looking.

In this setting an analog expression of (6) can be derived as

$$\widehat{\pi}_t = \frac{\omega}{\phi}\widehat{\pi}_{t-1} + \frac{\beta\theta}{\phi}E_t\widehat{\pi}_{t+1} + \frac{(1-\omega)(1-\theta\beta)(1-\theta)}{\phi}A\widehat{s}_t, \tag{7}$$

with $\phi = \theta + \omega\left[1-\theta(1-\beta)\right]$. When $\omega = 0$ this expression is equivalent to the pure forward looking Phillips curve and thus equal to (6) as long as $\xi = 0$.

Finally, note that the explanatory variables are the same across the two Phillips curve specifications, the only difference is the way how the structural parameters appear in the two equations. While the interpretation of θ is the same, the parameters ξ and ω have a different meaning depending on the particular model that both try to rationalize a lagged inflation term in the Phillips curve.

3 Econometric Methodology

We now present our empirical model and discuss how we can conduct inference about the structural parameters of the Phillips curve model discussed above. In this analysis we take a limited information approach. This has the great advantage that we do not have to fully specify a hole general equilibrium model including the nature of the forcing variable. Instead, we can leave part of the model unspecified and only have to consider a single equation. As it is known from traditional simultaneous equation framework, full information methods may be more efficient, but may also be more sensitive to specification errors since errors in one equation spread over to other equations as well.[8]

Our empirical model is given by

$$\widehat{\pi}_t = \gamma_b \widehat{\pi}_{t-1} + \gamma_f \widehat{\pi}_{t+1} + \lambda \widehat{s}_t + u_t, \tag{8}$$

where $u_t = \eta_t - \gamma_f \left(\widehat{\pi}_{t+1} - E_t \widehat{\pi}_{t+1} \right)$. Note that expected future inflation $E_t \widehat{\pi}_{t+1}$ has been replaced by its realization $\widehat{\pi}_{t+1}$, whereas the expectation error $(\widehat{\pi}_{t+1} - E_t \widehat{\pi}_{t+1})$ is part of the residual u_t. The coefficients γ_b, γ_f and λ depend in nonlinear form on the structural parameters $(\beta, \theta, \xi, \alpha, \epsilon)$ in the partial indexation model or on

[8]Examples for ML techniques to estimate hybrid Phillips curve specifications include Fuhrer (1997), Lindé (2005) and Jondeau and Le Bihan (2006). See Jondeau and Le Bihan (2008) for discussion of properties of different estimators.

$(\beta, \theta, \omega, \alpha, \epsilon)$ in the model with rule-of-thumb firms.

Since the residual u_t is correlated with $\widehat{\pi}_{t+1}$ (unless there exist forecast errors of future inflation) an instrumental variables estimator is needed in order to guarantee unbiased results. We employ a Generalized Method of Moments (GMM) estimator proposed by Hansen (1982) that is suited for dynamic non-linear models in order to estimate the structural model parameters. This approach is frequently applied to estimate intertemporal asset pricing models.[9] In our setting where non-linearity is present via the parameters but not within the variables this procedure can be given a 2SLS interpretation. First, regress the endogenous right-hand-side variables on the instrument set. Second, use the predicted values and perform non-linear least squares where the variables on the right-hand side are replace by their projections.

The GMM approach is now also very frequently applied to estimate the parameters of the Calvo model. Examples include Galí and Gertler (1999), Galí et al. (2001) and Eichenbaum and Fisher (2007). First, we set up the orthogonality conditions for the partial indexation model (6). We use two different specifications that differ in the way how functions are normalized.[10] These are given by

$$u_t^1 = \widehat{\pi}_t - \frac{\xi}{1+\beta\xi}\widehat{\pi}_{t-1} - \frac{\beta}{1+\beta\xi}\widehat{\pi}_{t+1} - \frac{(1-\theta\beta)(1-\theta)}{(1+\beta\xi)\theta}A\widehat{s}_t, \tag{9}$$

$$u_t^2 = (1+\beta\xi)\widehat{\pi}_t - \xi\widehat{\pi}_{t-1} - \beta\widehat{\pi}_{t+1} - \frac{(1-\theta\beta)(1-\theta)}{\theta}A\widehat{s}_t, \tag{10}$$

[9] See Hansen and Singleton (1982) for an early example.

[10] It is well known that for finite samples the two-step GMM as well as the iterated GMM estimator is sensitive to transformations of the orthogonality conditions (see i.e. Hall, 2005). Unless the model is not misspecified, the two different normalizations should lead to approximately similar results.

with the orthogonality conditions

$$E_{t-1}\left\{u_t^i\left(\beta,\theta,\xi\right)\mathbf{z_{t-1}}\right\}=0 \tag{11}$$

for $i=1,2$. $\mathbf{z_{t-1}}$ is the vector of instruments that are assumed to be orthogonal to the error term u_t^i (under the rationality assumption). Note that $\mathbf{z_{t-1}}$ does only include instruments dated $t-1$ or earlier in order to rule out simultaneity issues. This also guarantees that the information is already available at time t due to a potential publication lag.

From (9) and (10) it follows that θ and A (and thus also α and ϵ) cannot be separately identified. So we are only able to estimate θ, the parameter that is of most interest, given reasonable values of α and ϵ which cannot be tested explicitly. To identify the remaining parameters β, θ and ξ we need at least three valid instruments.

For the model with rule-of-thumb firms, similar orthogonality conditions can be formulated. They only differ with respect to the functional form of the parameters. The two normalizations are given by

$$\begin{aligned} u_t^{'1} &= \widehat{\pi}_t-\frac{\omega}{\phi}\widehat{\pi}_{t-1}-\frac{\beta\theta}{\phi}\widehat{\pi}_{t+1}-\frac{(1-\omega)(1-\theta\beta)(1-\theta)}{\phi}A\widehat{s}_t, && (12)\\ u_t^{'2} &= \phi\widehat{\pi}_t-\omega\widehat{\pi}_{t-1}-\beta\theta\widehat{\pi}_{t+1}-(1-\omega)(1-\theta\beta)(1-\theta)A\widehat{s}_t. && (13)\end{aligned}$$

Again, the orthogonality conditions can be formulated as

$$E_{t-1}\left\{u_t^{'i}\left(\beta,\theta,\omega\right)\mathbf{z_{t-1}}\right\}=0 \tag{14}$$

for $i = 1, 2$ with $\phi = \theta + \omega [1 - \theta(1 - \beta)]$. Everything else is comparable with the partial indexation model.

4 Data and empirical implementation

Our sample period is 1973.1 - 2004.4. While data before 1973 are principally available, we take this date as starting point since it marks the end of the fixed exchange rate regime of the Bretton Woods system. This is also associated with a change in monetary policy that got more independent from external influences. Inflation is measured as the quarterly annualized change in the GDP deflator. From the production function (1) it follows that real marginal cost are proportional to the labor income share in national income. The labor share is defined as the total wage bill ($W_t N_t$) divided by nominal GDP ($P_t Y_t$). The variable $\widehat{s}_t$ is constructed as the percentage deviation of the labor share from its sample average (see figure 2).[11]

Since in our Phillips curve specification the term A cannot be separately identified, we have to calibrate α and ϵ in an economic reasonable way. We set α, the output elasticity with respect to capital, equal to 0.3 that usually done for the German economy (i.e. Dreger and Schumacher, 2000). More controversial is the calibration of the elasticity of substitution among different goods. For the definition of the steady state mark-up μ, it follows that the elasticity of substitution can be redefined as $\epsilon = \frac{\mu}{\mu - 1}$. We consider a steady-state mark-up of 10% ($\mu = 1.1$) as our baseline value (as it was done by Galí et al., 2001; Eichenbaum and Fisher, 2007). This corresponse to $\epsilon = 11$.

[11]This is the measure proposed by Galí and Gertler (1999), Galí et al. (2001) and Sbordone (2002).

A next very crucial issue is concerned with the instrument vector $\mathbf{z_{t-1}}$. To be a valid instrument, variables have to fulfill two important characteristics. First, they have to be uncorrelated with the error term (which is the orthogonality condition). Second, they have to be correlated with the variable they have to instrument (that is the relevance condition). Both conditions have to be fulfilled to obtain reliable point estimates and confidence intervals of our model parameters. So the first practical challenge is to decide which variables should be included into the instrument set. In principle any variable dated $t-1$ and earlier may be considered as instrument since under rational expectations it fulfills the orthogonality conditions. This leaves us with a potentially infinite set of possible variables that could be used as instruments. But as was early recognized by Tauchen (1986) and Kocherlakota (1990) instruments should be used quite parsimonious.[12]

To deal with problems of redundant instruments we apply a two-step approach where we try to cull out those variables that are really relevant. As a starting point we consider a wide range of possible instruments that include important macroeconomic indicators. This potential instrument list contains Galí and Gertler's (1999) instrument set with inflation, real marginal cost, real-time detrended GDP, wage inflation, commodity price inflation, and the long-short interest rate spread. Further we include as an additional instrument the short interest rate (defined as the three month bill). For the variables $\widehat{\pi}_t$ and $\widehat{s}_t$ we allow for a potential lag length of five quarters; for the remaining candidate variables we use a maximal lag length of 2. The first step of instrument selection contains a preselection of possible instruments within a VAR. Therefore, the two endogenous variables $\widehat{\pi}_{t+1}$ and $\widehat{s}_t$ are

[12] Tauchen (1986) finds in a simulation study that the inclusion of additional instruments that are not relevant or only marginally relevant leads to increasing bias of the parameter estimates.

regressed on all potential instruments. This specification can be formalized as

$$\begin{bmatrix} \widehat{\pi}_{t+1} \\ \widehat{s}_t \end{bmatrix} = \nu + \sum_{i=1}^{L_1} A_i y_{t-i} + \sum_{j=1}^{L_2} B_i x_{t-j} + u_t, \tag{15}$$

with ν a deterministic term, $y_{t-i} = [\widehat{\pi}_{t-i} \ \widehat{s}_{t-i}]'$ and x_{t-i} the vector of all other predetermined variables with lag i. The maximal lag length is $L_1 = 5$ and $L_2 = 2$.

After estimating the full model we apply a model reduction procedure that works through a sequential elimination of regressors in order to obtain a model that lead to the smallest information criterion.[13] We base the selection procedure on two selection criteria (AIC and SC). Accordingly, we end up with restrictions on A_i and B_i that determine our instrument sets $\mathbf{z_{t-1}}(c^{AIC})$ and $\mathbf{z_{t-1}}(c^{SC})$, where c^j denotes which elements of the candidate set are included in a particular moment condition. Besides the two instrument sets based on the information criteria, we also take Galí et al.'s (2001) set as a benchmark.

Thus, we have three candidate instrument sets with the following size:

- AIC based instrument set: that includes 14 of 21 potential instruments (see sec 1),
- SC based instrument set: that includes 11 instruments (see sec 1),
- Galí et al.'s (2001) instrument set: that includes inflation with lags $t-1$ to $t-5$, labor share, wage inflation and output gap from $t-1$ to $t-2$ (all

[13] The sequential elimination of regressors strategy works through sequentially delete those regressors which lead to the largest reduction of the specified criterion until no further reduction is possible. This procedure is implemented in the software package JMulTi (see Lütkepohl and Krätzig, 2004; Brüggemann and Lütkepohl, 2000). Note, that the selection mode takes the inflation term with one lag as given, since this term also enters as a predetermined variable into our Phillips curve specification.

together 11 instruments),

The sensitiveness of our results with respect to different instrument sets should indicate whether there are problems with redundant instruments or weak instruments.

As a second step we also apply a moment selection test after we performed the GMM estimation to evaluate our preselection based on model reduction techniques. This strategy is based upon the relevance condition. Therefore we use a moment selection criterion proposed by Hall, Inoue, Jana and Shin (2007). This criteria is defined as

$$RMSC(c) = ln\left[\left|\hat{V}_{\theta,T}(c)\right|\right] + (|c| - p)\, ln(T^{1/3})/T^{1/3} \tag{16}$$

where $\hat{V}_{\theta,T}(c)$ is the covariance matrix of the model parameters conditional on the instrument set c. The second term is a BIC-type penalty term with T the sample size and p the number of parameters to be estimated. The idea is to select the instrument vector that minimizes this criterion. Since the relevance condition can be interpreted as statement about the asymptotic variance of the estimator, the sample analog is the natural basis to construct an information criterion. Hall et al. (2007) show that the natural logarithm of the determinant of the variance can serve for this purpose. Note that this procedure only works when there are no weak instrument problems present. Meaning that it is necessary to have at least some variables that are considerably correlated with the endogenous variables they have to instrument.

5 Estimation Results

In this section we present the results of the structural model and their robustness to several empirical aspects. First, we check for the sensitivity with respect to different instrument sets and with respect to different orthogonality conditions. As pointed out above the instrument relevance is essential for the reliability of GMM point estimates and confidence intervals. So, we report estimation results with the instrument set used by Galí et al. (2001) and compare that with those that are based on a preselection as discussed in section (4).

For the model with partial indexation (Table 2) the results do not differ much across orthogonality conditions and instrument sets (an exception are the results based on the second orthogonality condition with GGL's instrument set with inflated standard errors). The RMSC criteria that is applied to evaluate the relevance of the instrument set favors the SC based instrument set. With this particular instrument set the point estimate for θ varies from 0.61 to 0.69. These are different form zero and different from one as well (this is necessary for the model to hold at least from an economic perspective). The estimates display reasonable values for θ which implies that firms re-optimize prices about every 3 quarters. In addition, the J test does not indicate any problems for this specification. The point estimates of the discount factor β are somewhere around one which is also plausible form an economic point of view. We find little evidence for the full indexation scheme ($\xi = 1$) as proposed by Christiano et al. (2005) since the coefficient tests reject this hypothesis. Furthermore, we do not even find a significant role for partial indexation in general impliing that ξ is not different from zero. This finding favors a pure forward looking specification without a lagged inflation term.

The evidence is more mixed by looking at the model with rule-of-thumb firms (Table 3). Here, the results differ considerably with respect to the way how the orthogonality condition is formulated. This is particularly true for point estimates of θ where the first orthogonality condition produces similar results as the model with partial indexation. But with orthogonality condition (2) the estimated values for θ are much smaller. Additionally, the J test is significant for that specification. This casts doubt on the estimation results based on condition (2), but also on the model in general. Since this sensitivity to the normalization of the orthogonality condition may indicate some form of model misspecification. The estimates for the remaining parameters do not differ much from the ones obtained with the partial indexation scheme. Again, the discount factor is close to one and the backward looking inflation term (ω in this specification) seems to be unimportant.

We further check the sensitivity of our results for different assumption about firm specific marginal cost. We first show how the estimates of θ change when we assume a markup of 25% ($\mu = 1.25$) instead of 10% as assumed in our baseline specification (Table 4). As expected, the point estimates for θ rise slightly whereas the remaining parameters are in principal uneffected. But again the estimates of θ stay in an economic meaningful range and cannot be rejected on empirical grounds. Next we give up the assumption of firm specific marginal cost and assume equal marginal cost accross firms ($A = 1$) as in the baseline model of Galí and Gertler (1999). This leads to further rise of estimated parameter θ to about 0.8 in the partial indexation model and to 0.6 to 0.8 in the model with rule-of-thumb firms (this implies an average frequency of price-reoptimization between 3 and 9 quarters). This specification still coincides with a sticky price framework which manifests in a higher degree of price rigidity. From an empirical point of view we cannot favor one spefication over the other which only differs with respect to the way how firm specific marginal cost from average marginal cost. Since the model is compatible with different assumptions about firm specific marginal cost it also introduces an additional source of uncertainty in estimating θ and the frequency of re-optimization.

These findings also hold for the case when we restrict the different model specification to the pure forward looking specification and a discount factor of $\beta = 0.99$ (Table 7). Therefore we employ a likelihood ratio type test where we check whether the imposed restrictions can be rejected (Table 5 and 6). The tests indicate that the restrictions cannot be rejected and are thus imposed. With these restrictions both model specifications (the partial indexation model as well as the model with rule-of-thumb firms) are the same. This specification is purely forward-looking (does not include a lagged inflation term) where the coefficients are non-linear functions of the parameter θ. Again we can construct two different orthogonality conditions that differ with respect to the particular normalization. As with the rule-of-thumb specifications the estimation results for θ differ considerably. But when we impose less real rigidity ($A \to 1$) the values for θ converge slightly, but the frequency of re-optimization of price changes is always twice as high as in the orthogonality condition (2) compared to the first one.

Finally, we also have a look at the sensitivity of inflation to our marginal cost variable. We denote the reduced form coefficient in front of the marginal cost variable with λ (which is defined as $\lambda = \frac{(1-0.99\theta)(1-\theta)}{\theta}A$). To evaluate whether λ is significant we use the point estimates for θ and its variance to construct standard errors for λ with the delta method. The results are displayed in Table 8 and are quite heterogeneous with respect to parameter values as well as for their significance level. For the first specification we find small values of λ that are not significant at conventional levels. The opposite is true for the second orthogonality condition. There we find larger values for λ that are always significant. These result cast doubt whether marginal cost is indeed the driving variable for inflation or whether the labor share is the correct measure of marginal cost.

6 Robustness Analysis

We now consider some kind of robustness analysis within our GMM framework. Since it was sometimes argued that the New Keynesian Phillips curve omits further inflation lags (i.e. Jondeau and Le Bihan, 2006), we check whether our basic results hold when we put three more lags of inflation into our Phillips curve specifications. When the former specification is correct additional lags should not be a determinant of actual inflation (they should be solely a predictor of future inflation).

Tables 9 and 10 shows the results of these augmented specifications. Although the general interpretation continues to hold, we find that in either case the estimate of θ is higher than based on our baseline specification. The other parameters do not considerably change and still lie inside a plausible range. Another important feature, the differences between the orthogonality conditions (1) and (2) in the rule-of-thumb model, is still present and is not overcome by the inclusion of the additional variables. Some of these lags indeed turn out to be significant determinates of inflation (specifically the fourth lag). Similarly to Galí and Gertler (1999) we also test whether the sum of these coefficients are different from zero. We use a Wald test and find no evidence that the sum of additional lags are important.

Overall, the inclusion of additional lags does not lead to a complete rejection of our original specification. But it further shows how sensitive estimates of θ are to small changes of the model. Particularly the significance of the fourth lag of inflation calls for an extension of the baseline model that displays this pattern.

7 An identification robust alternative

So far our analysis rests on the assumption that our instrument set is sufficiently correlated with the endogenous variables under consideration. This means we have assumed that our regression analysis does not suffer from weak instrument problems. But as shown by a vast literature, the presence of weak instruments may cause serious distortions in standard IV point estimates, hypothesis tests and confidence intervals (see Stock, Wright and Yogo, 2002, for an overview of problems caused by weak instruments and some recommendations to deal with it.). Several authours, including Ma (2002), Nason and Smith (2005), Dufour, Khalaf and Kichian (2006) and Mavroeidis (2006) provide evidence that weak instrument problems may be present in standard GMM estimations of the new Keynesian Phillips curve.

That is why we have to highlight potential problems with weak instruments or weak identification in our estimation strategy as well. This is done in more detail in this section. In section 4 we have already tried to selection our instruments on some kind of objective method in order to choose only instruments that are really correlated with the endogenous regressors. But this does by no means help to screen whether weak instrument problems may be present in our analysis. As shown by Mavroeidis (2005) standard pre-tests of identification (or weak instrument problems) are inappropriate in our setting. So we reevaluate our GMM results with an identification robust method that is fully robust to problems induced by weak instruments and weak identification. Therefore, we stick to a non-linear variant of the Anderson-Rubin Statistic as suggested by Stock and Wright (2000). They show that identification robust confidence sets can be obtained from the continuous-updating GMM (CUE) objective function.[14] In the linear simultaneous equations model these so called S-sets are asymptotically equivalent to confidence sets constructed by inverting the Anderson-Rubin test statistic.

As shown by Dufour (2003) the AR statistic is well suited for validating a structural model, since it is not only robust to the presence of weak instruments, but it is also robust to model misspecifications like overidentification and thus provides an alternative to the standard J test. S-sets also share the characteristic of identification-robust procedures as described in Dufour (1997) which require that whenever parameters are not identified, the results should lead to uninformative and thus unbounded confidence sets. S-sets contains all parameter values for which the joint hypothesis $\vartheta = \vartheta_0$ and that the overidentifying conditions are valid. So, whenever the model is misspecified and the overidentifying conditions are invalid, the S-sets can be null. With weak instruments (or irrelevant instruments), the S-sets can contain the entire parameter space. While this is a favored property of this test because it ensures robustness to many pitfalls, it also needs some caution in interpreting the results of the model. Particularly, when S-sets are small this can be because the model is correctly specified or because it is misspecified but

[14] The continuous-updating GMM estimator was invented by Hansen, Heaton and Yaron (1996). As opposed to the standard two-step GMM estimator, the CUE evaluates the weight matrix at the same parameter value as the orthogonality conditions.

does not lead to a full rejection.[15]

Now we turn back to our model specifications where the objective function of the CUE is given by

$$S(\vartheta) = \left[\frac{1}{T}\sum_{t=1}^{T}\phi_t(\vartheta)\right]' V(\vartheta)^{-1}\left[\frac{1}{T}\sum_{t=1}^{T}\phi_t(\vartheta)\right] \tag{17}$$

with ϑ the parameter vector of interest; $\phi_t(\vartheta) = u_t(\beta,\theta,\omega)\,\mathbf{z_{t-1}}$ with $u_t(\beta,\theta,\omega)$ as defined in (9) and (12) and $\mathbf{z_{t-1}}$ the vector of instruments. Note that the CUE is invariant to transformations of the orthogonality condition, so we do not have to consider this differentiation. $V(\vartheta)$ is defined as a HAC estimator to allow for serial correlation as well as heteroskedasticity in the residuals. This coincides with the two-step estimator used above.

We now check whether our baseline GMM results hold when we use S-sets as suggested by Stock and Wright (2000). First, we examine whether our GMM point estimates are also included the S-sets. This should be the case when the model is correctly specified and there are no weak instrument problems present. We start with the pure forward looking specification where we test the null hypothesis of whether β and θ are $(0.99, 0.58)$ or $(0.99, 0.18)$ which corresponds to the GMM estimates of Table (7) with $A = 0.175$. According to Stock and Wright (2000) $S(\beta_0,\theta_0) \xrightarrow{D} \chi^2_k$, where $S(\beta_0,\theta_0)$ is the objective as defined above evaluated at the true parameter values. Table (11) reports the results of this test type. The results indicate that problems with the orthogonality conditions may be present since the test rejects the the hypothesis for both GMM point estimates, at least at the 10%

[15]This may become relevant when there are many instruments. In this case the power of the test might be too low to reject a potentially misspecified model.

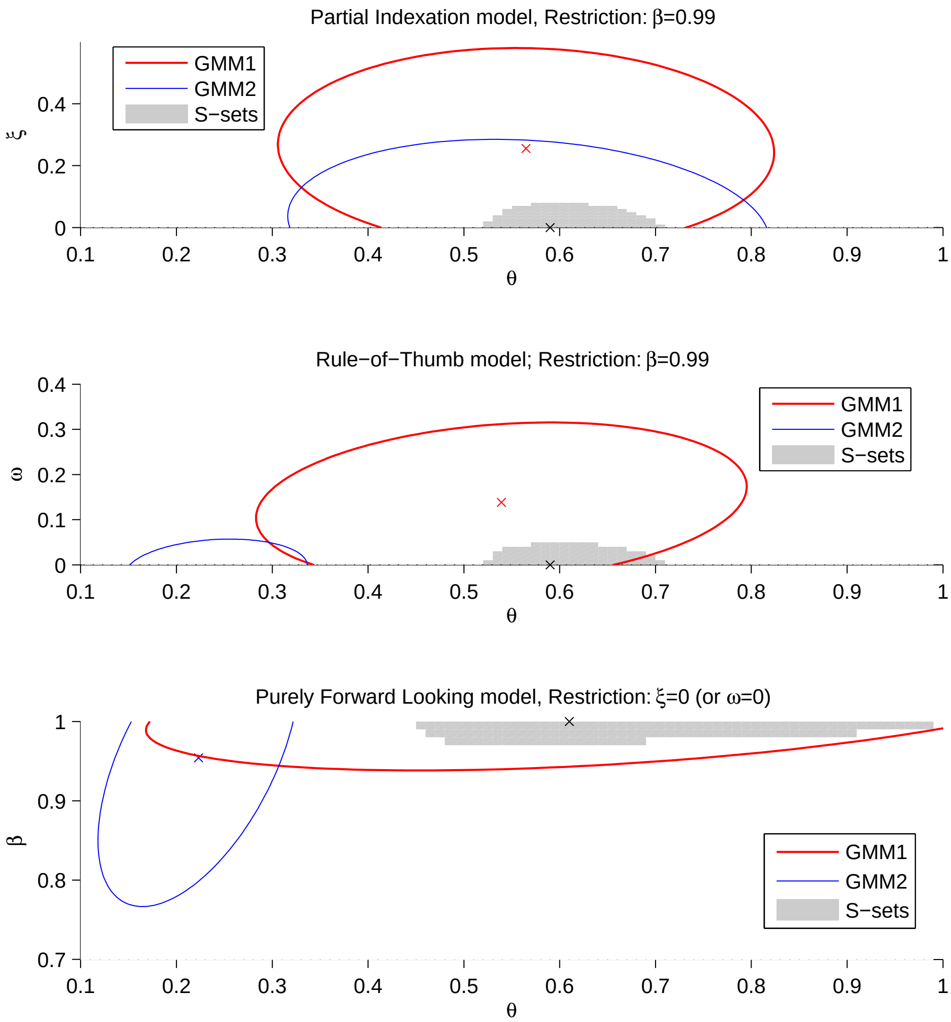
level.[16] Now, we ask whether there exists a value of the parameter vector for which the model is not rejected.[17] Given this particular instrument set (based on the SC) we find no parameter combination that lies inside the 90% S-set. That means that the confidence interval is empty and we have to reject the model. As mentioned above this indicates that the overidentifying conditions are invalid. So there may be one or more variables in our instrument set that do not fulfill the orthogonality condition. A natural candidate is a variable that is measured in $t-1$, so agents do not use this kind of information. We exclude some of the instruments from period $t-1$ variable-by-variable and find out that the wage inflation is the variable that causes the AR type test to reject the model. So we exclude that variable and redo the analysis.

With our adjusted instrument set the S-sets are non-empty and can be used for inference of our model. Figure 1 shows the 90% confidence regions obtained with that method along with the standard GMM results and their 90% confidence ellipsis for different model specifications. Generally, we find rather small S-sets irrespectively which particular model is used or which restrictions are imposed. For the partial indexation model, the computed S-set (only computed for economic reasonable paramter values between 0 and 1) lies completly inside the two GMM ellipses. The regions all include the null of parameter ξ, impliing that this value is not significantly different from zero. The results based upon the S-sets also imply a parameter value for θ of about 0.6 which translates into a frequency of price re-optimization of 2.5 quarters. The GMM results are similar. This estimate is in line

[16] Although the test is more in favour of the first estimate, denoted by $\hat{\theta}_{GMM1}$. But we follow Stock and Wright and take the 90% S-set as our final decision criterium.

[17] The paramter space that we consider involves all possible values in the range of 0 to 1. In the search process all values between this range are evaluated with increments of 0.01.

Figure 1: Joint 90% S-sets and 90% GMM confidence ellipses for different specifications



with Coenen et al. (2007) who find an average frequency of price re-optimization of 2 quarters for the German economy, although with a different estimation strategy and a higher degree of real rigidities. The results based upon the rule-of-thumb model are in principle identical, even though the GMM estimates again differ quite substancially with respect to the transformation of the orthogonality condition. As mentioned above, S-sets are invariant to the normalization of the orthogonality conditions because they are based upon the CUE. From an empirical point of view, we cannot distinguish between the partial indexation model and the rule-of-thumb. But, as shown throughout, the GMM estimates are sensitive to transformation of the orthogonality condition. That becomes very obvious in the rule-of-thumb model where the second specification leads to a large bias.

Since the hybrid version of the Phillips curve is rejected we concentrate once more on the pure forward looking specification. While the S-set for this specification is again quite small, it already includes values for θ between 0.45 up to 1. This implies that the uncertainty about θ is quite high when no further restrictions on β are imposed. This also translates into the sensitivity of inflation to marginal cost. When $\theta = 1$ prices are never re-optimized and thus do not respond to chances in marginal cost. As long as we cannot rule out the case that θ is equal to one, the model is economically meaning less and can be also seen as rejected.

Taken together, we do not find much evidence that the German NKPC is weakly identified. But, we show that identification robust inference with the nonlinear Anderson-Rubin Statistic may help to detect model misspecifications not indicated by the standard J test. Another advantage to the more conventional two-step GMM estimator is the fact, that the S-sets are based upon the CUE and thus not sensitive to transformations of the orthogonality conditions.

8 Conclusion

This paper evaluates standard New Keynesian Phillips Curve specifications for Germany within a limited information framework. Besides the standard GMM estimation and test procedures, we also apply identification robust techniques. The presented evidence clearly favors a purely forward looking inflation equation which is in contrast to most other countries. The average frequency of price reoptimization of firms is estimated to be about two and three quarters, given a plausible degree of real rigidity in the German economy. While these estimates seem plausible from an economic point of view, the uncertainty around these estimates are very large and also consistent with perfect nominal price rigidity where firms never reoptimize their prices. This also casts doubt concerning the labor share as driving variable for inflation.

In contrast to previous studies, we do not detect problems with weak identification, but we do find some evidence that the model might be misspecified.

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Appendix

Figure 2: Data series for Germany

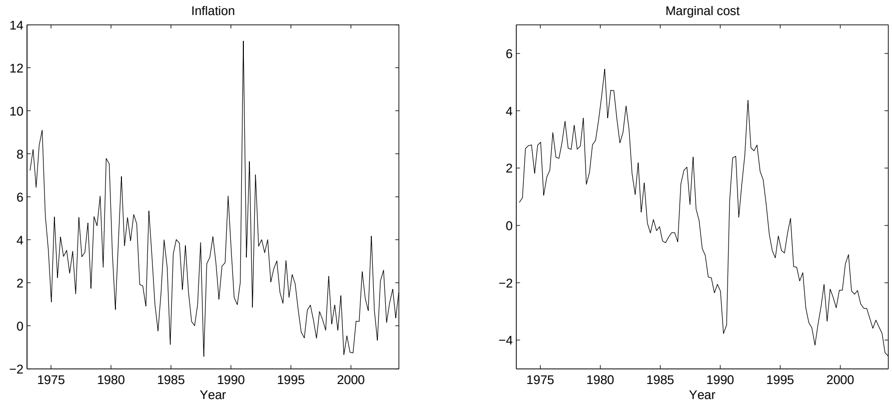

Table 1: Instrument selection based on Information Criteria

	AIC		SC	
	$\widehat{\pi}_{t+1}$	$\widehat{s}_t$	$\widehat{\pi}_{t+1}$	$\widehat{s}_t$
$\widehat{\pi}_{t-1}$	-0.012	0.060	-0.030	0.042
	[-0.12]	[1.34]	[-0.29]	[0.94]
$\widehat{s}_{t-1}$	-0.008	0.825	-0.012	0.824
	[-0.06]	[14.14]	[-0.09]	[13.71]
$\widehat{\pi}_{t-3}$	0.409	0.012	0.397	0.014
	[5.09]	[0.36]	[4.86]	[0.41]
$\widehat{\pi}_{t-4}$	0.125	0.099	0.109	0.088
	[1.53]	[2.82]	[1.33]	[2.50]
$\widehat{s}_{t-4}$	0.146	0.191	0.151	0.232
	[0.76]	[2.32]	[0.78]	[2.80]
$\widehat{\pi}_{t-5}$	0.003	0.150	-0.006	0.139
	[0.04]	[4.12]	[-0.07]	[3.73]
$\widehat{s}_{t-5}$	-0.120	-0.144	-0.102	-0.177
	[-0.70]	[-1.96]	[-0.59]	[-2.37]
y^{gap}_{t-1}	2.382	1.670	2.588	1.608
	[2.62]	[4.30]	[3.13]	[4.52]
$(r^l - r^s)_{t-1}$	0.277	-0.687	-0.066	-0.163
	[0.54]	[-3.15]	[-0.64]	[-3.72]
Δw_{t-1}	0.124	-0.031	0.137	-0.021
	[2.21]	[-1.30]	[2.46]	[-0.86]
r^s_{t-1}	0.518	-0.479	0.147	-0.076
	[1.16]	[-2.52]	[2.18]	[-2.61]
Δp^{comm}_{t-2}	0.009	0.004		
	[1.85]	[1.97]		
$(r^l - r^s)_{t-2}$	-0.324	0.515		
	[-0.66]	[2.45]		
r^s_{t-2}	-0.397	0.391		
	[-0.90]	[2.09]		
AIC	1.1094		1.1168	
SC	1.7429		1.6146	

Notes: t-statistics in brackets.

Table 2: Partial Indexation model (unrestricted)

Instruments		β	θ	ξ	J	RMSC
GGL's set	(1)	0.996	0.632	0.309	8.877	-9.76
		(0.084)	(0.216)	(0.153)		
		[0.000]	[0.004]	[0.044]	[0.353]	
	(2)	1.047	0.980	-0.333	11.095	-1.63
		(0.040)	(54.43)	(0.072)		
		[0.000]	[0.986]	[0.000]	[0.196]	
AIC based	(1)	1.035	0.646	0.294	9.787	-9.18
		(0.062)	(0.217)	(0.147)		
		[0.000]	[0.003]	[0.045]	[0.550]	
	(2)	1.039	0.743	-0.178	12.125	-10.14
		(0.038)	(0.367)	(0.094)		
		[0.000]	[0.043]	[0.059]	[0.354]	
SC based	(1)	1.030	0.611	0.248	8.454	-10.51
		(0.058)	(0.181)	(0.156)		
		[0.000]	[0.001]	[0.112]	[0.390]	
	(2)	1.036	0.690	-0.182	10.820	-11.63
		(0.038)	(0.270)	(0.097)		
		[0.000]	[0.011]	[0.059]	[0.212]	

Notes: Standard errors in round brackets and p-values in square brackets. Rows (1) and (2) correspond to the two specifications of the two specifications of the orthogonality conditions eqs (9) and (10) in the text, respectively. A 5-lag Newey-West HAC estimate was used. Sample period: 1973:1-2004:4.

Table 3: Rule-of-Thumb model (unrestricted)

Instruments		β	θ	ω	J	RMSC
GGL's set	(1)	0.997	0.601	0.186	8.877	-11.11
		(0.072)	(0.224)	(0.097)		
		[0.000]	[0.007]	[0.056]	[0.353]	
	(2)	0.836	0.121	-0.019	16.050	-17.05
		(0.160)	(0.027)	(0.015)		
		[0.000]	[0.000]	[0.214]	[0.042]	
AIC based	(1)	1.030	0.621	0.182	9.787	-10.47
		(0.055)	(0.223)	(0.095)		
		[0.000]	[0.005]	[0.057]	[0.550]	
	(2)	0.883	0.181	-0.018	17.971	-16.20
		(0.102)	(0.033)	(0.020)		
		[0.000]	[0.000]	[0.353]	[0.082]	
SC based	(1)	1.026	0.590	0.146	8.454	-11.87
		(0.052)	(0.184)	(0.092)		
		[0.000]	[0.001]	[0.111]	[0.390]	
	(2)	0.908	0.178	-0.019	16.945	-16.83
		(0.104)	(0.035)	(0.020)		
		[0.000]	[0.000]	[0.340]	[0.031]	

Notes: Standard errors in round brackets and p-values in square brackets. Rows (1) and (2) correspond to the two specifications of the two specifications of the orthogonality conditions eqs (12) and (13) in the text, respectively. A 5-lag Newey-West HAC estimate was used. Sample period: 1973:1-2004:4.

Table 4: Sensitivity to different values of A

	Partial indexation model				Model with Rule-of-Thumb firms			
	β	θ	ξ	J	β	θ	ω	J
$\alpha = 0.3$, $\mu = 1.25 \longrightarrow \epsilon = 5$, $A = 0.3182$								
(1)	1.030	0.690	0.248	8.454	1.027	0.669	0.165	8.454
	(0.058)	(0.151)	(0.156)		(0.053)	(0.158)	(0.101)	
	[0.000]	[0.000]	[0.112]	[0.390]	[0.000]	[0.000]	[0.101]	[0.390]
(2)	1.036	0.755	-0.182	10.820	0.970	0.335	-0.033	15.695
	(0.038)	(0.151)	(0.156)		(0.080)	(0.050)	(0.037)	
	[0.000]	[0.001]	[0.097]	[0.212]	[0.000]	[0.000]	[0.377]	[0.047]
$A = 1$								
(1)	1.030	0.805	0.248	8.454	1.028	0.788	0.195	8.454
	(0.058)	(0.096)	(0.156)		(0.055)	(0.106)	(0.118)	
	[0.000]	[0.000]	[0.112]	[0.390]	[0.000]	[0.000]	[0.112]	[0.390]
(2)	1.036	0.846	-0.182	10.820	1.030	0.635	-0.078	13.410
	(0.038)	(0.135)	(0.156)		(0.053)	(0.051)	(0.069)	
	[0.000]	[0.000]	[0.097]	[0.212]	[0.000]	[0.000]	[0.255]	[0.099]

Notes: see above.

Table 5: Restrictions in the Partial Indexation model

$H_0: \beta = 0.99,\ \xi = 0$	LR-Test	p-value
(1)	0.0581	0.9714
(2)	4.3360	0.1144

Table 6: Restrictions in the Rule-of-Thumb model

$H_0: \beta = 0.99,\ \omega = 0$	LR-Test	p-value
(1)	5.9409	0.0513
(2)	2.1815	0.3360

Table 7: Frequency of Re-optimization (Restrictions: $\beta = 0.99$, $\xi = 0$, $\omega = 0$)

	$A = 0.1750$		$A = 0.3182$		$A = 1$	
	θ	$\frac{1}{1-\theta}$	θ	$\frac{1}{1-\theta}$	θ	$\frac{1}{1-\theta}$
(1)	0.577	2.36	0.664	2.98	0.795	4.88
	[0.34,0.81]		[0.46,0.87]		[0.65,0.94]	
(2)	0.179	1.22	0.326	1.48	0.607	2.54
	[0.11,0.24]		[0.24,0.41]		[0.52,0.69]	

Notes: J test never rejects any model.

Table 8: Sensitivity to marginal cost (Restrictions: $\beta = 0.99$, $\xi = 0$, $\omega = 0$)

$$\lambda = \frac{(1-0.99\theta)(1-\theta)}{\theta}A$$

	$A = 0.1750$		$A = 0.3182$		$A = 1$	
	λ	J	λ	J	λ	J
(1)	0.055	11.236	0.055	11.236	0.055	11.236
	(0.042)		(0.042)		(0.042)	
	[0.195]	[0.339]	[0.195]	[0.339]	[0.195]	[0.390]
(2)	0.663	14.873	0.445	14.136	0.259	13.054
	(0.178)		(0.117)		(0.072)	
	[0.000]	[0.137]	[0.000]	[0.137]	[0.001]	[0.221]

Notes: Standard errors are computed with the delta method.

Table 9: Partial Indexation model with additional Lags

	β	θ	ξ	ϕ_2	ϕ_3	ϕ_4	$H_0 : \phi_2 + \phi_3 + \phi_4 = 0$	J
(1)	0.793	0.846	0.141	0.0911	-0.196	0.275	2.227	5.609
	(0.146)	(0.428)	(0.109)	(0.093)	(0.081)	(0.069)		
	[0.000]	[0.048]	[0.193]	[0.327]	[0.015]	[0.000]	[0.527]	[0.468]
(2)	0.825	0.868	0.046	0.113	-0.217	0.289	2.568	6.367
	(0.131)	(0.507)	(0.099)	(0.093)	(0.089)	(0.074)		
	[0.000]	[0.087]	[0.641]	[0.226]	[0.015]	[0.000]	[0.463]	[0.383]

Notes: SC based instrument set used (plus inflation at the second lag).

Table 10: Rule-of-Thumb model with additional Lags

	β	θ	ξ	ϕ_2	ϕ_3	ϕ_4	$H_0 : \phi_2 + \phi_3 + \phi_4 = 0$	J
(1)	0.798	0.831	0.118	0.0911	-0.196	0.275	2.227	5.609
	(0.146)	(0.454)	(0.094)	(0.093)	(0.081)	(0.069)		
	[0.000]	[0.067]	[0.211]	[0.327]	[0.015]	[0.000]	[0.527]	[0.468]
(2)	1.081	0.273	0.016	0.0120	-0.105	0.059	0.398	13.180
	(0.186)	(0.082)	(0.039)	(0.031)	(0.033)	(0.044)		
	[0.000]	[0.001]	[0.690]	[0.526]	[0.001]	[0.177]	[0.941]	[0.059]

Notes: SC based instrument set used (plus inflation at the second lag).

Table 11: AR type test of the estimated parameters

Null Hypothesis	Test Statistic	p-value
$H_0 : \beta_0 = 0.99, \theta_0 = \hat{\theta}_{GMM1} = 0.58$	19.28	0.056
$H_0 : \beta_0 = 0.99, \theta_0 = \hat{\theta}_{GMM2} = 0.18$	33.10	0.001

Notes: The test is evaluated with the CUE objective function. The SC based instrument set is used. A Newey-West HAC estimate with 5 lags was used. Sample period: 1973:1-2004:4.