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Cross-sectional evidence on state-dependent versus time-dependent price setting

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Abstract

We empirically analyze aggregate price setting by means of a nonparametric representation of the structural New Keynesian Phillips curve derived from Calvo (1983) pricing for a large cross-section of 14 industrialized economies. State-dependence of the Calvo parameter is tested in a functional-coefficient regression framework. We reject state-invariant pricing. Moreover, problems reported in the extant literature of insignificant and implausible estimates of the Phillips-curve relation are mitigated in the state-dependent specification.

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1. Introduction

The most widely used price-updating mechanism in theoretical macroeconomic models is the Calvo (1983) staggered contracts model where a constant Calvo parameter determines a (fixed) share of randomly drawn firms which adjust prices at each time instance. This is referred to as time-dependent price adjustment. Despite its popularity, constancy of the Calvo parameter is criticized as a rather restrictive description of price setting (Wolman 1999, Cogley and Sbordone 2005, Canova, 2006, and Fernández-Villaverde and Rubio-Ramírez 2008).

For time-dependent price-setting models firms' price changing decisions are independent of the economic state, but depend exclusively on time. This assumption is vulnerable to the Lucas critique. The theoretical literature describes several settings in which, e.g., firms have an incentive to respond to higher inflation rates with more frequent price adjustments (Romer 1990, Dotsey et al. 1999, and Golosov and Lucas 2007). Another often described influence on price adjustment is inflation uncertainty (IU henceforth). In this case, however, incentives are ambiguous. While IU may cover extraordinary increases in firms' markup over marginal cost, it could also encourage search effort and price monitoring by customers (Bénabou 1992). The former creates an incentive to increase the frequency of price adjustments, while the latter creates an incentive to decrease it.

In this paper, we implement a testing procedure by means of a nonparametric representation of the standard structural form New Keynesian Phillips curve (NKPC). This functional-coefficient (FC) regression model allows to express the Calvo parameter as a functional of observable factor variables such as inflation, IU, or both factors simultaneously (Danziger 1983). We focus on inflation and IU, since these variables are in many theoretical studies described as potential factors which may affect price updating, following Romer (1990), Bénabou (1992), and Danziger (1983) inter alia. Moreover, since central banks are typically held accountable in the first place for the dynamics of inflation and IU, this choice also allows to establish a clear-cut relation between changes in price setting and the decisions of monetary policy. The FC regression we propose nests both state- and time-dependent pricing rules. The case of time-dependent pricing corresponds to testing the null hypothesis of parameter constancy against the alternative hypothesis of inflation- or IU-induced price revisions.

The contribution of this paper is twofold. First, we document state-dependence of the Calvo parameter with respect to inflation and IU for 14 industrialized economies. Second, we contribute to the literature of single equation estimation of the NKPC via the generalized method of moments (GMM), pioneered by Galí and Gertler (1999). We show that our state-dependent NKPC estimation mitigates the recurring finding of insignificant and implausible NKPC parameter estimates (Wolman 1999), which have led to doubts about the empirical validity of the NKPC.

Few empirical macroeconomic studies document instability of the Calvo parameter. Cogley and Sbordone (2005) find minor differences in the Calvo parameter across regimes estimating a generalized NKPC. In a New Keynesian model, Canova (2006) reports evidence similar to Cogley and Sbordone (2005), while Fernández-Villaverde and Rubio-Ramírez (2008) find that fluctuations in the Calvo parameter are negatively correlated with inflation. In contrast to these studies, we retain the standard NKPC framework of Galí and Gertler (1999). To test for state-dependence of the Calvo parameter, we employ a formal and robust statistical method which also acknowledges the role of potential heteroscedasticity in the NKPC disturbances.

Our results are important for the analysis of monetary policy. First, output effects of monetary shocks are typically weaker and less persistent for state-dependent models relative to time-dependent models (Golosov and Lucas 2007). Second, the welfare implications under state- and time-dependent approaches coincide only under the very restrictive assumption of an efficient steady state (Lombardo and Vestin 2008).

2. Empirical Approach

The NKPC which allows for a FC relationship of the Calvo parameter, i.e. $\theta = \theta(\omega_{i,t-1})$, reads as:

$$\pi_{it} = \beta\pi_{i,t+1} + \frac{(1-\theta(\omega_{i,t-1}))(1-\theta(\omega_{i,t-1})\beta)}{\theta(\omega_{i,t-1})} s_{it} + \varepsilon_{it}, \;\; i = 1, ..., N, \; t = 1, ..., T, \qquad (1)$$

where π_{it} denotes inflation in quarter t and country i, s_{it} real marginal costs and $\beta < 1$ the discount parameter. Equation (1) is a generalization of the standard NKPC (Galí and Gertler 1999) along the lines of Dotsey et al. (1999), who were among the first to derive a NKPC representation with a state-variant Calvo parameter which nests the conventional time-dependent NKPC as a restrictive special case. In equation (1) the Calvo parameter $\theta(\omega_{i,t-1}) \in [0, 1]$ depends on two predetermined variables: $\omega_{i,t-1} = (w^{(1)}_{i,t-1}, w^{(2)}_{i,t-1})'$, where $w^{(1)}_{i,t-1} = \pi_{i,t-1}$ and $w^{(2)}_{i,t-1} = IU_{i,t-1}$. IU is measured as $IU_{i,t-1} = |\Delta\pi_{i,t-1}| = |\pi_{i,t-1} - \pi_{i,t-2}|$, the absolute error of a random walk forecast, one of the most successful devices to predict inflation (Canova 2007). To account for different scales of $\pi_{i,t-1}$ and $IU_{i,t-1}$, $w^{(\bullet)}_{i,t-1}$ enters (1) in standardized form, i.e. $w^{(\bullet)}_{i,t-1} = \widetilde{w}^{(\bullet)}_{i,t-1}/\sigma^{(\bullet)}(\widetilde{w})$, with $\sigma^{(\bullet)}(\widetilde{w}) = \sqrt{(1/(N-1))\sum_i (w^{(\bullet)}_{i,t-1} - \bar{w}^{(\bullet)}_{t-1})^2}$, $\bullet \in \{1, 2\}$.

2.1 Estimation

We test for functional dependence of the price-adjustment parameter on $\pi_{i,t-1}$ and $IU_{i,t-1}$ in the framework of FC estimation (Cai et al. 2000). Thereby we also capture cross-sectional specialities in the functional relation $\theta(\omega)$[1], e.g. due to distinct economies' institutional characteristics. To account for potential endogeneity of s_{it}, we apply GMM (Galí and Gertler 1999) to estimate (1), such that

$$\hat{\theta}(\omega) = \arg\min_{\theta} Q(\theta, K_h(\omega)), \qquad (2)$$

with $Q(\cdot)$ denoting the GMM objective function

$$Q(\theta, K_h(\omega)) = \bar{m}(\cdot)'\Phi\bar{m}(\cdot). \qquad (3)$$

In (3), $K_h(\omega) = K(\omega/h)/h$ represents the logistic kernel function, which is a function of the "bandwidth" $h > 0$. Following "Scott's rule", we set $h = 1.06(NT)^{-1/6}$. Moreover, Φ represents a positive definite matrix and $\bar{m}(\cdot)$ the vector of empirical moments

$$\bar{m}(\theta, K_h(\omega)) = (1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T} z_{i,t-1}\varepsilon_{it} K_h(w^{(1)}_{i,t-1} - w^{(1)}) K_h(w^{(2)}_{i,t-1} - w^{(2)}), \qquad (4)$$

[1] We abbreviate $\omega_{i,t-1} = \omega$ in the following.

which is evaluated over the range of $w^{(1)}_{i,t-1}$ and $w^{(2)}_{i,t-1}$. In (4), $z_{i,t-1}$ denotes a vector of instrument variables.

2.2 Inference

We test $H_0 : \theta(\omega) = \theta$, i.e. a constant Calvo parameter. Rejecting H_0 in favor of a FC $\theta(\omega)$ implies state-dependence. In applications of FC models, inference is often based on resampling residuals (Cai et al. 2000). However, inflation series, and consequently also the disturbances from (1), often feature conditional heteroscedasticity (Engle 1982). Since inference based on heteroscedastic disturbances might lead to spurious conclusions, we employ a "factor-based bootstrap" (FB) (Herwartz and Xu 2009). Instead of resampling $\hat{\varepsilon}_{it}$, FB relies on resampling factors $\omega = (w^{(1)}, w^{(2)})$. The procedure is implemented as follows:

i) Based on (1), estimate $\hat{\theta}(\omega)$ and, say, 1000 bootstrap counterparts $\hat{\theta}(\omega^*)$ by sampling 2-tuples $\omega^* = (w^{(1*)}, w^{(2*)})$, with replacement, from $(w^{(1)}_{i,t-1}, w^{(2)}_{i,t-1})$.

ii) Reject H_0 if, for any ω, $\hat{\theta}(\omega)$ is outside the $(1 - c) \times 100\%$-quantile range of the bootstrap estimates from a.), given some confidence level c.

Random sampling distorts any potential relation between θ and ω. Hence, $\hat{\theta}(\omega^*)$ satisfy H_0 by construction. If H_0 holds, $\hat{\theta}(\omega)$ and $\hat{\theta}(\omega^*)$ are close to each other, whereas values $\hat{\theta}(\omega)$ outside the interval suggest that H_0 should be rejected.

2.3 Data

We employ quarterly, seasonally adjusted series of real GDP, Y_{it}, the implicit output deflator, IPD_{it}, and unit labor costs, ULC_{it}, for economies $i, i = 1, ..., N$: Australia, Belgium, Canada, Finland, France, Italy, Japan, Netherlands, New Zealand, Portugal, Spain, Sweden, UK, and US, ($N = 14$), drawn from the OECD database. We denote $y_{it} = \ln(Y_{it})$, inflation as $\pi_{it} = 400 \times (p_{it} - p_{i,t-1})$ with $p_{it} = \ln(IPD_{it})$, for $t = 1, ..., T$ representing quarters 1961Q3 to 2011Q4, ($T = 201$). Unobservable marginal costs are approximated by the labor share such that $s_{it} = s^*_{it} - \bar{s}_i$, where $s^*_{it} = ulc_{it} - p_{it}$, and $ulc_{it} = \ln(ULC_{it})$. The steady-state measure $\bar{s}_i$ is computed as $\bar{s}_i = (1/T)\sum_{t=1}^{T} s^*_{it}$. As instrument variables in (4), we use $z_{i,t-1} = (\tilde{y}_{i,t-1}, \tilde{y}_{i,t-2})'$, where $\tilde{y}_{i,t-1}$ denotes the output gap (cf. Galí and Gertler 1999) that is obtained by using a one-sided HP filter, i.e. as $\tilde{y}_{i,t} = y_{it} - \bar{y}_{it}$, where trend output, $\bar{y}_{it}$, is computed recursively, using information up to and including time instance t at each step.[2]

[2]This one-sided filtering approach follows Dufour et al. (2006). The authors argue that lagged values of full-sample filtered output gaps are, by construction, related to future information and therefore not an appropriate instrument variable. One-sided filtering methods are not subject to such timing violations.

Country	ARCH(1)	ARCH(4)	Country	ARCH(1)	ARCH(4)
AUS	41.70	52.07	JPN	18.89	26.01
BEL	9.24	24.41	NLD	32.37	111.74
CAN	28.61	33.40	NZL	41.31	53.47
ESP	34.94	42.81	PRT	38.44	52.26
FIN	74.89	102.17	SWE	76.26	81.09
FRA	42.67	51.31	UK	77.99	79.46
ITA	26.25	42.10	US	43.99	51.42
$\chi^2_{0.95}$- crit. val.:	3.84	9.49		3.84	9.49

Table 1: ARCH-LM diagnostics $\mathrm{ARCH}(\cdot) = TR^2$ from $\hat{\varepsilon}^2_{it} = \gamma_1 \hat{\varepsilon}^2_{i,t-1} + \beta\pi_{i,t+1} + \kappa s_{it} + v_{it}$ and $\hat{\varepsilon}^2_{it} = \gamma_1 \hat{\varepsilon}^2_{i,t-1} + \gamma_2 \hat{\varepsilon}^2_{i,t-2} + \gamma_3 \hat{\varepsilon}^2_{i,t-3} + \gamma_4 \hat{\varepsilon}^2_{i,t-4} + \beta\pi_{i,t+1} + \kappa s_{it} + v_{it}$ for $i = 1, ..., N$.

3. Results

First, diagnostic statistics highlight the merits of the selected model. Second, we report and discuss results.

3.1 Model diagnostics

The appeal of using the FB approach is demonstrated by the residual diagnostics from (1) as reported in Table 1. Apart from cross-sectional heterogeneity, the variance of NKPC residuals ε_{it} is likely to exhibit time-conditional heteroscedasticity. This is confirmed by economy-specific ARCH-LM statistics in Table 1. As Fernández-Villaverde and Rubio-Ramírez (2008) point out, such effects might lead to spurious conclusions regarding state-dependence of θ.

In addition, a J-test for overidentifying restrictions obtains a value close to zero, indicating weak exogeneity of $z_{i,t-1}$.

A further diagnostic test is to assess the relevance of the selected instrument variables. As discussed by Stock et al. (2002) or Mavroeidis et al. (2014), the GMM estimation approach we apply in the setting of the NKPC might suffer from weak identification. This problem arises if instrument- and explanatory variables are not strongly related. To examine this issue, we employ an F-test for joint significance of the instrument variables in a regression of s_{it} on $z_{i,t-1}$. The test indicates significant explanatory content of the instrument variables, taking a value of $F = 12.019$, which exceeds the "rule-of-thumb-" threshold of $F = 10$ discussed by Stock et al. (2002). Thus, we conclude that our empirical approach might not be overly vulnerable to the problem of weak identification.

3.2 State-dependence of the NKPC

In the following, we discuss the potential dependence of the NKPC on ω. Figure 1 depicts estimates of $\theta(\omega)$ (solid lines) as a function of either $w^{(1)}$ or $w^{(2)}$ for fixed values of the respective other variable, for example, $\hat{\theta}(w^{(1)}|w^{(2)} = q^{(2)}_{\star})$, where $q^{(2)}_{\star}$ denotes quantiles with $\star \in \{20\%, 50\%, 80\%\}$ of the empirical distribution of $w^{(2)}_{i,t-1}$. Dashed lines represent 90%-FB-bootstrap confidence intervals. State-invariance (H_0) is rejected for any ω where $\hat{\theta}(\omega)$ lies outside the interval. For low to

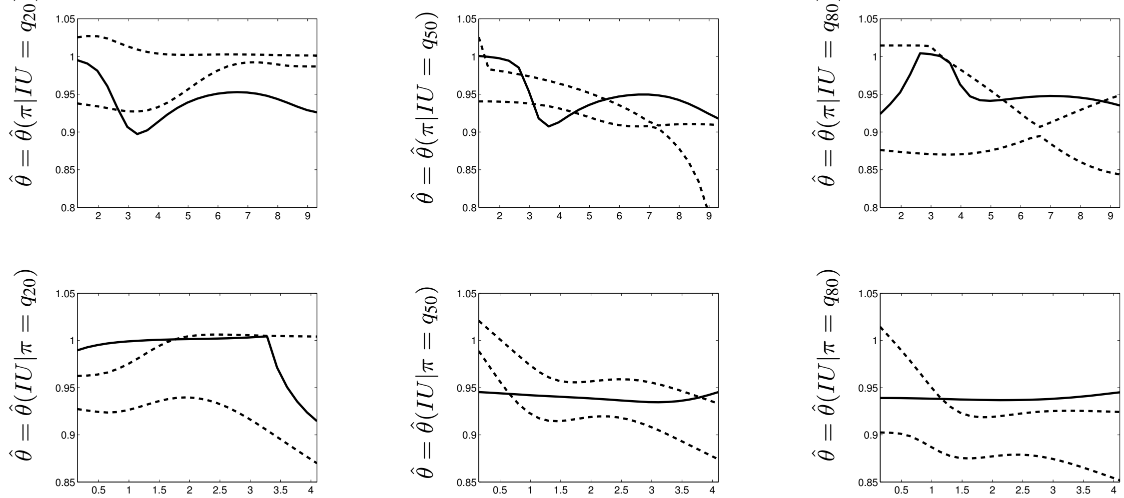

Figure 1: 2D-plots of functional-coefficient estimates.
Estimates $\theta(w^{(\bullet)}|w^{(\circ)} = q_\star^{(\circ)})$ conditional on $\circ, \bullet \in \{\pi, IU\}$ for $\star \in \{20\%, 50\%, 80\%\}$.

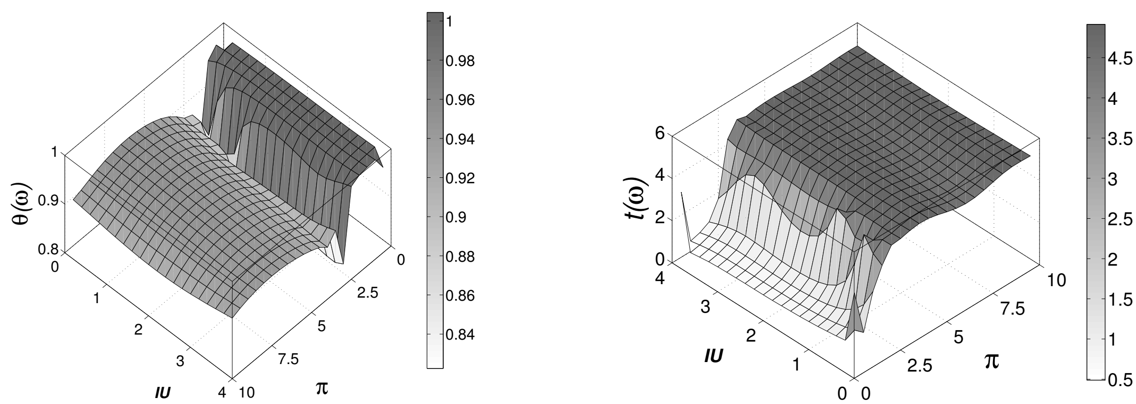

Figure 2: 3D-plots of functional-coefficient estimates.
Estimates for $\theta(\omega)$ are depicted in the left plot, t-stats on the right hand side.

moderate levels of inflation and $IU \in \{q_{20}, q_{50}\}$, estimates $\hat{\theta}(\omega)$ in Figure 1 confirm the theoretical prediction $\partial\theta(\omega)/\partial\pi < 0$. Changes in $\hat{\theta}(\pi|IU)$ for $IU = q_{80}$ and $\pi > 5\%$ are relatively small. Significant changes in $\hat{\theta}(IU|\pi)$ are also limited to particular regions of the range of IU. This is also in line with microdata evidence from Klenow and Kryvtsov (2008). In contrast, we do not find evidence for a uniform sign of the IU impact, in line with Bénabou (1992), who argues that both signs are plausible.

Next, the joint influence of π and IU on $\hat{\theta}(\omega)$ is depicted in the 3D-plot in the left part of Figure 2. While $\hat{\theta}(\omega)$ is highest for low π, it decreases at intermediate levels for $\pi \approx 3\%$. The plot also shows that variation in $\hat{\theta}(\omega)$ due to IU is confined to cases where $\pi < 4\%$. However, this range of π is currently most frequently observed in the considered economies. The size of $\hat{\theta}(\omega)$ is close to estimates reported in Fernández-Villaverde and Rubio-Ramírez (2008).

Finally, the recurring finding of implausible Phillips-curve estimates might be due to the assumption of θ as constant (Wolman 1999). We examine this claim by specifying the reduced-form

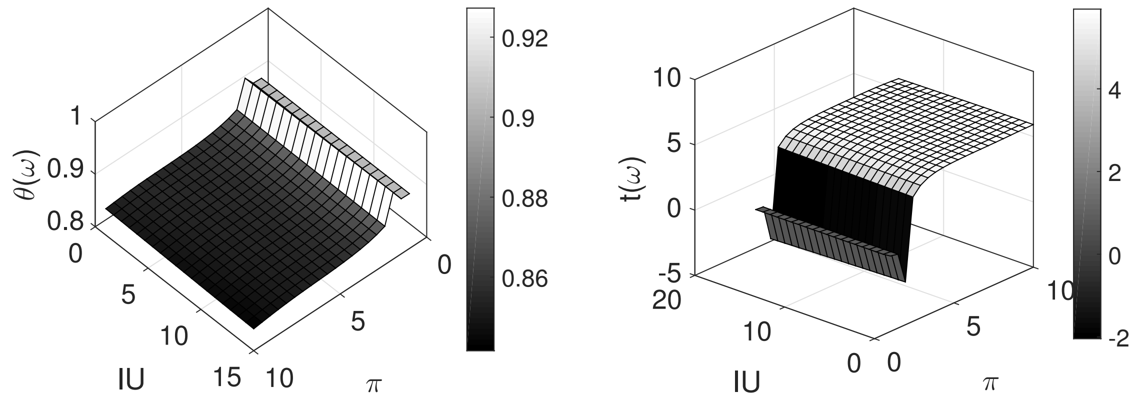

Figure 3: 3D-plots of $\hat{\theta}(\omega)$ with alternative inflation uncertainty measure $IU_{i,t} = (\Delta\pi_t)^2$.
Estimates for $\theta(\omega)$ are depicted in the left plot, t-stats on the right hand side.

parameter $\kappa = ((1-\theta)(1-\theta\beta))/\theta$ as $\kappa = \kappa(\omega)$. State-dependent t-statistics regarding $\kappa(\omega)$, denoted $t(\omega)$, are shown in the right plot in Figure 2. Allowing for state-dependence of $\kappa(\omega)$ obtains highly significant $t(\omega)$-statistics over almost the entire range of ω. On the other hand, the state-invariant t-statistic is insignificant and equals $t_{H_0} = 1.04$. Coefficient estimates $\hat{\kappa}(\omega)$ vary between ≈0.02 and ≈0.23 for cases where $t(\omega)$ is significant. This suggests that conventional marginal cost measures are in line with theoretically plausible estimates once state-dependence, i.e. $\kappa = \kappa(\omega)$, is allowed for.

3.3 Robustness

In this Section, we assess the robustness of the findings with respect to respecifications of the model and of the estimation procedure.[3] First, results may depend on the way how the unobservable IU is quantified. There exists no consensus on the most suitable way to measure IU (Batchelor and Dua 1996). In the first step, we compare outcomes for $|\Delta\pi_{i,t-1}|$ as a measure of IU by those for an alternative quantification. The left graph in Figure 3 shows a 3D-surface plot of $\hat{\theta}(\omega)$ for the case when $IU_{i,t-1} = (\Delta\pi_{i,t-1})^2$ is employed as a measure of inflation uncertainty. The figure shows that the conclusions from Section 3.2 regarding state-dependence of $\hat{\theta}(\omega)$ remain essentially unchanged. The most pronounced changes in $\hat{\theta}(\omega)$ are found with respect to the inflation rate, which leads to a steady decrease in $\hat{\theta}(\omega)$ over almost the entire support of π. In contrast, the influence of IU appears to be limited also in case of the alternative IU measure. Moreover, the right graph in Figure 3 depicts state-variant t-statistics. The figure highlights that the influence of the marginal cost measure on inflation is clearly significant for most values of the state variables also if IU is quantified by $(\Delta\pi_{i,t-1})^2$.

A second reexamination of the empirical approach is concerned with the choice of instrument variables. Since the estimate of $\tilde{y}_t$ may depend to some extent on the choice of the filtering method, it is tempting to compare the results from Section 3.2 to the ones obtained if unfiltered, i.e. directly observable data are employed as additional instrument variables. Figure 4 shows results corresponding to those in Figure 1 if $z_t = (\tilde{y}_{i,t-1}, \tilde{y}_{i,t-2})'$ is replaced by

[3] We are grateful to an anonymous referee for suggesting these robustness check.

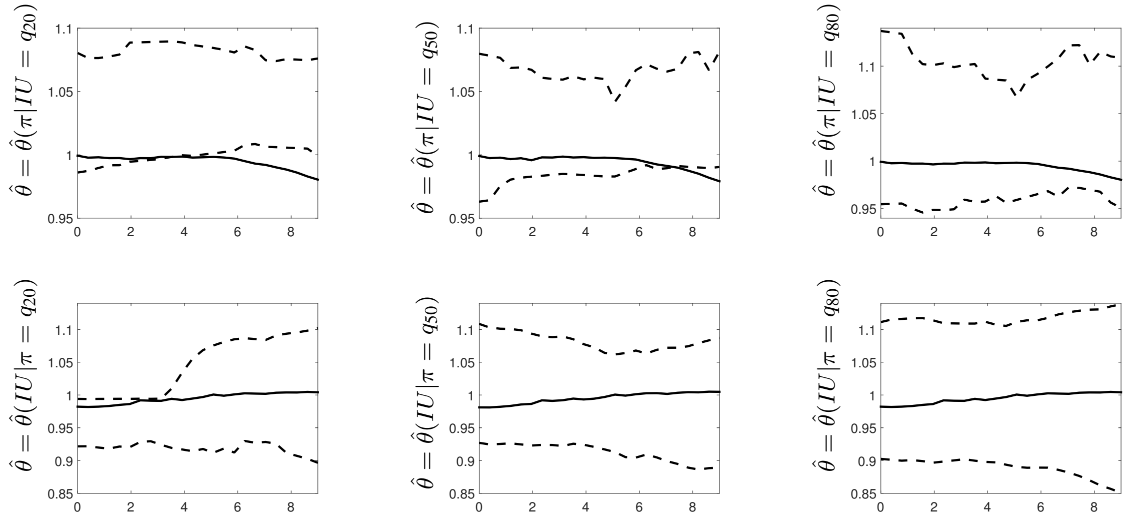

Figure 4: 2D-plots of functional-coefficient estimates $\bar{\hat{\theta}}(\omega)$, on average across distinct choices of instrument variables. For further descriptions, see Figure 1.

$z_t^* = (\tilde{y}_{i,t-1}, ..., \tilde{y}_{i,t-4}, \pi_{i,t-1}, ..., \pi_{i,t-4})'$. To show that the findings are robust with respect to subset choices of this larger instrument variable set, the Figure shows the mean $\bar{\hat{\theta}}(\omega) = (1/J) \sum_{j=1}^{J} \hat{\theta}(\omega)_j$, over $j = 1, ..., J$ subset combinations of the 8 instrument variables, where $J = \sum_{k=1}^{8} 8!/(8-k)!k! = 255$. Similarly, we obtain averages across the confidence bands that are computed for each single estimate of $\hat{\theta}(\omega)$ given a particular combination of instrument variables.

4. Summary

We document significant state-dependence of the price adjustment frequency in the New Keynesian Phillips curve framework. Moreover, state-dependent estimates are more in line with theory than the ones obtained assuming a constant frequency of price adjustment. Several alternative specification choices regarding the estimation strategy underline the robustness of the empirical findings. We conclude that treating the Calvo (1983) price-updating frequency as a structural parameter may be overly restrictive.

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