How to disappear completely: non-linearity and endogeneity in the new keynesian wage Phillips curve

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How to disappear completely: non-linearity and endogeneity in the New Keynesian Wage Phillips Curve

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Abstract

We use a three-regime threshold regression model to assess the ability of the New Keynesian Wage Phillips Curve (NKWPC) to describe wage inflation in the U.S. over the 1965-2018 period. Non-linearity is clearly supported by the data and it easily resists an endogeneity correction. However, this correction exposes more clearly the shortcomings of the NKWPC as a successful description of wage dynamics in the extreme phases of the business cycles, when unemployment is either low or high. In both cases it becomes completely flat.

Keywords: Phillips curve; wage rigidity; threshold regression; endogeneity.

JEL codes: C22, E24, E31, E32.

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1 Introduction

The U. S. missing economic phenomena department has been very busy as of late: after the initial missing deflation, price and wage inflation are missing for several years. The disconnect between unemployment and price inflation has been reported and studied in Albuquerque and Baumann (2017) and Stock and Watson (2018), *inter alia*. Our main concern is with the recent upward nominal wage rigidity. Our approach to study the relation between unemployment and wage inflation in the U.S. is a non-linear version of the New Keynesian Wage Phillips Curve (NKWPC).

As Donayre and Panovska (2016) we also adopt a three-regime threshold regression model. However, we account for the endogeneity issues that threat estimation consistency. While non-linearity is clearly supported by the data and easily resists the endogeneity correction, it is not sufficient to keep the NKWPC afloat as the negative relation between wage inflation and unemployment that should be observed in the last years remains missing even after controlling for price indexation and for lagged unemployment (and, of course, for the non-linearity itself).

In the next section we briefly present the NKWPC and the least squares based evidence for non-linearity. Section 3 describes our approach to the endogeneity issues and the corresponding results. Section 4 concludes the paper.

2 Non-linearity in the NKWPC

Our starting point is Galí's (2011) reduced form but microfounded wage equation:

$$\pi_t^w = \alpha + \rho\pi_{t-1}^p + \psi_0\hat{u}_t + \psi_1\hat{u}_{t-1}, \tag{1}$$

where π_t^w and π_t^p denote wage and price inflation, respectively, $\hat{u}_t = u_t - u^n$ is cyclical unemployment, defined as the difference between the observed and the natural rate of unemployment, and the parameters are either functions of structural parameters or of a mixture of structural and autoregressive parameters of a stationary AR(2) process assumed for the unemployment rate; at least for the U.S., one must observe $\psi_0 < 0$ and $\psi_1 > 0$. This specification is derived in a staggered nominal wage setting and represents the New Keynesian paradigm for the wage equation, in the same vein as the original Phillips (1958) curve, relating wage inflation with unemployment. Although simple, the relation is now dynamic. It is the most representative New Keynesian Wage Phillips Curve (NKWPC).

To bypass its pitfalls, recently it has been augmented, either through its information set (e.g., Byrne and Zekaite, 2019) or by means of the number of equations, in the structural VAR framework (as in Galí and Gambetti, 2019). Motivated by evidence concerning parameter instability and the widely reported downward nominal rigidity, and as in Donayre and Panovska (2016, DP), we take a different route, investigating the existence of threshold type non-linearities.

We use quarterly data from FRED. Wage and price inflation are computed as the four quarter growth of earnings for production and non-supervisory workers and of the consumer price index, respectively. To compute cyclical unemployment we use the Congressional Budget Office (CBO) estimate for the natural rate of unemployment. The effective sample ranges from 1965Q1 to 2018Q4,i.e., $T = 216$.

The testing strategy in Hansen (1999) led us to adopt a three-regime threshold model:

$$\pi_t^w = \boldsymbol{x_t'\beta_1} I(q_t \leq \gamma_1) + \boldsymbol{x_t'\beta_2} I(\gamma_1 < q_t \leq \gamma_2) + \boldsymbol{x_t'\beta_3} I(q_t > \gamma_2) + e_t, \qquad (2)$$

where $\boldsymbol{x}_t = (1 \ \pi_{t-1}^p \hat{u}_t \ \hat{u}_{t-1})'$, $\boldsymbol{\beta}_j = (\alpha_j \ \rho_j \ \psi_{0,j} \ \psi_{1,j})$, $I(.)$ denotes the indicator function and γ_1 and γ_2 are the lower and upper thresholds of the threshold variable q_t. Estimation is carried out using sequential conditional least squares (CLS), which is OLS conditional on the estimated thresholds ($\hat{\gamma} = (\widehat{\gamma}_1, \widehat{\gamma}_2)$), obtained as minimizers of the sum of squared residuals function over a grid of admissible values [1].

By extending this grid search over the possible candidate variables for q_t the

[1] We have estimated the threshold parameters using the sequential "one-at-a-time" method proposed in Hansen (1999) inspired in the change point estimation literature and analysed in Gonzalo and Pitarakis (2002).

optimal threshold variable is also selected. Since our regime switching regression aims to capture possible changes over different macroeconomic conditions, we have used indicators that measure the participation in the labour market. Therefore, as candidates for that role, we have considered up to three lags of the unemployment rate, cyclical unemployment and variations in unemployment ($\Delta u_t = u_t - u_{t-1}$). Differently from DP, who selected $q_t = u_{t-1}$, the CLS grid-search procedure chose the current unemployment rate as the optimal threshold variable, so we set $q_t = u_t$ in our empirical application.

Both to test for linearity and to select the number of regimes we have used the standard Hansen's (1999) F_{il} statistics, $i < l$, i denoting the number of regimes of the null hypothesis and l the one of the alternative (i.e., $i = 1, 2$ and $l = 2, 3$, respectively). Table 1 contains the statistics F_{12}, F_{13} and F_{23} and their bootstrapped p-values, obtained under both homoskedastic and heteroskedastic errors. Both linearity tests clearly reject the linear model. Also, the sequential testing procedure clearly and robustly favours the three-regime model.

Table 1: Tests for linearity and for the number of regimes

	Test statistic	Homoc. Boot. p-value	Heter. Boot. p-value
F_{12}	45.72	0.00	0.00
F_{13}	73.94	0.00	0.00
F_{23}	23.28	0.02	0.03

Notes: the statistics F_{12} and F_{13} refer to the test of the linear model against a two and three-regime threshold model, respectively; the statistic F_{23} is used to test for remaining nonlinearity in the two-regime model. "Homoc. Boot." and "Heter. Boot." represent homoskedasticity and heteroskedasticy bootstrap, respectively.

Table 2 contains the estimation results of the three-regime NKWPC. Wage inflation dynamics are split into a low ($u_t \leq 5.70$), intermediate ($5.70 < u_t \leq 7.63$) and high unemployment regimes ($u_t > 7.63$), i.e., the estimated thresholds are $\widehat{\gamma}_1 = 5.70$ and $\widehat{\gamma}_2 = 7.63$. 95% confidence intervals, obtained via the inversion of the likelihood ratio statistic (Hansen, 2000) are also presented next to each threshold estimate.

By analyzing the slope coefficients we can observe that, besides economically meaningful, price indexation is always statistically significant, specially in the second regime. However, Galí's predictions concerning the signs of the coefficients of cyclical unemployment are confirmed (and significantly so) only in the middle regime. In the extreme phases of the business cycle the estimated coefficients for cyclical unemployment either have the incorrect sign or are not statistically different from zero.

Table 2: CLS estimation results for the three-regime threshold model

	Threshold Variable		u_t	$\hat{\gamma}_1 = 5.70$ $[5.30, 5.87]$			SSR		193.32
	trimming param.		0.15	$\hat{\gamma}_2 = 7.63$ $[7.37, 7.67]$			Residual Variance		0.89
	Regime 1 ($u_t \leq 5.70$)			Regime 2 ($5.70 < u_t \leq 7.63$)			Regime 3 ($u_t > 7.63$)		
Variable	Estim.	SE	SE*	Estim.	SE	SE*	Estim.	S.E.	SE*
Constant	2.06	0.11	0.17	2.20	0.39	0.63	3.56	1.15	1.70
π^p_{t-1}	0.44	0.04	0.05	0.62	0.05	0.07	0.38	0.06	0.09
$\hat{u}_t$	-0.81	0.36	0.57	-2.30	0.47	0.70	0.34	0.26	0.40
$\hat{u}_{t-1}$	-0.01	0.37	0.59	1.44	0.42	0.60	-0.72	0.23	0.32
Observ.(% tot.)	110	51%		71	33%		35	16%	
Reg. Variance	0.66			1.20			1.01		

Notes: the trimming parameter, which defines the minimum number of observations in each regime, is set to 0.15. SE* denotes the HAC standard error (SE).

Although somewhat informal and indirect, an important way to validate the adoption of a non-linear model is to assess its forecasting performance in relation to simpler, linear models. Therefore, we run a simple out-of-sample simulation forecasting exercise to analyze the accuracy of the linear, and the two and three-regime specifications of the NKWPC. We simulate one-step-ahead forecasts by re-estimating each model over an increasing window of observations. The initial window covers the sample up to either 2016Q4 or 2015Q4 and it is sequentially increased by one quarter at a time. In table 3 we report the root mean squared error (RMSE) and the mean absolute error (MAE) for the three models. This exercise clearly suggests that the accuracy of the three-regime NKWPC to forecast wage inflation is significantly better than that of the other two models. The evidence for the model of equation (2) is therefore reinforced.

Table 3: One-step-ahead simulated forecasting errors

	2017Q1-2018Q4 (last 2 years)				2016Q1-2018Q4 (last 3 years)			
	RMSE	%	MAE	%	RMSE	%	MAE	%
Linear model	0.89	100	0.86	100	0.74	100	0.64	100
2-regime model	0.85	96	0.82	96	0.72	98	0.63	99
3-regime model	0.74	83	0.72	84	0.62	84	0.54	84

3 Endogeneity

The estimates of Table 2 may be, however, affected by an endogeneity bias problem: a reverse causation relation between the variables of equation (1) is plausible to exist, particularly between π_t^w and unemployment, thereby inducing non-orthogonality between the regressors and its (implicit) error term, as well as between the threshold variable and that same error. This possibility is admitted in, e.g., Galí and Gambetti (2019) and it is forcefully presented in McLeay and Tenreyro (2018) for the case of the price Phillips curve. As McLeay and Tenreyro argue, as monetary authorities consider this last relation into account when setting the optimal policy rule, their efforts are directed to counteract it, thereby making it unidentifiable. Put simply and algebraically, endogeneity bias results from the joint and simultaneous determination of price inflation and unemployment that can be formalized through a two-equation system. Furthermore, although possibly less fragile than its sister price curve, the NKWPC is also liable to be affected by shocks that are correlated with both the dependent (π_t^w) and the independent (unemployment) variables.

Since the suspicion of endogeneity falls on both the regressors and the threshold variable, we had to resort to the method proposed by Kourtellos, Stengos and Tan (2016, KST) to obtain consistent estimates. Considering the case of a two-regime model as

$$y_t = \boldsymbol{x_t'\beta_1} I(q_t \leq \gamma) + \boldsymbol{x_t'\beta_2} I(q_t > \gamma) + \eta_t,$$

this method contains the following three steps:

1. First, estimate the reduced form equations relating the regressors and the threshold variable to the instruments (e. g., $\boldsymbol{x}_t = \boldsymbol{\Pi}'\boldsymbol{z}_t + \mathbf{v}_{xt}$ and $q_t = \boldsymbol{z}_t'\boldsymbol{\delta}_q + v_{qt}$, where $\boldsymbol{z}_t = (z_{t1}, z_{t2}, ..., z_{tp})'$ is a $p \times 1$ vector of instruments, such that $p \geq k$, k denoting the dimension of the $\boldsymbol{x}_t$ vector).

2. Second, estimate γ by concentrating (as usual) but minimizing a criterion function corresponding to a "structural model" that corrects the original model with bias correction terms for each regime (i.e., the inverse Mills ratios, that capture the correlation between the endogenous variable and the original error term).

3. Third, once $\widehat{\gamma}$ is obtained, estimate the slope parameters by GMM.

On the other hand, the extension to our three-regime model was achieved again using the sequential algorithm proposed in Hansen (1999) that was previously mentioned.

To specify an appropriate set of instruments to feed the KST method we resorted to three different approaches: a) the traditional or conventional, using lags of endogenous variables; b) a more modern approach, using a set of instruments appearing in the linear NK Phillips curve literature; c) and a pragmatic one, selecting those variables from the previous sets that appear to be better at reducing the endogeneity bias relatively to a "worst-case" benchmark estimator of the corresponding linear equation; towards this end we used the "effective F statistic" of Olea and Pflueger (2013) [2].

Although we have not searched exhaustively to minimize this statistic and tried to retain instruments from both previous sets, we acknowledge that there is an element of data mining in this procedure. However, it is based on a loosely defined selection method, built on the surrogate linear model version. Moreover, we must stress that the estimation results are largely insensitive to the particular set of instruments.

[2] This benchmark bias coincides with that of the OLS estimator when the errors are conditionally homoskedastic and serially uncorrelated. However, unlike the Stock and Yogo test which is appropriate in that case, the Olea and Pflueger test is robust to violations of both these hypotheses.

In table 4 we present the results obtained with this mixed set, consisting of π^p_{t-1}, π^p_{t-2}, $\widehat{u}_{t-1}$, $\widehat{u}_{t-2}$ and π^c_{t-1} which represents commodities price inflation lagged once.

Table 4: Estimation results with the KST method for the 3-regime model

	Threshold Variable	u_t	$\hat{\gamma}_1 = 5.70\ [4.13, 6.90]$			
	trimming param.	0.15	$\hat{\gamma}_2 = 7.63\ [7.20, 7.73]$			
	Regime 1 ($u_t \leq 5.70$)		Regime 2 ($5.70 < u_t \leq 7.63$)		Regime 3 ($u_t > 7.63$)	
Variable	Estim.	SE*	Estim.	SE*	Estim.	SE*
Constant	2.32	0.45	1.81	0.77	5.07	1.43
π^p_{t-1}	0.35	0.05	0.66	0.06	0.34	0.07
$\hat{u}_t$	0.29	0.65	-2.33	0.68	0.16	0.34
$\hat{u}_{t-1}$	-1.14	0.64	1.60	0.65	-0.86	0.27
Observ.(% tot.)	110	51%	71	33%	35	16%

Note: SE* denotes the HAC standard error (SE).

Besides a generalized and expected deterioration in estimated precision, the new results agree closely with those of table 2 in almost all the most relevant issues: for instance, a remarkable coincidence between the estimated threshold parameters, the statistical and economic relevance of price indexation across all regimes (and again, specially in the intermediate regime), the coherence with Galí's predicted coefficient signs only in the middle regime, etc. . The major differences concern the increased evidence for the flatness of the relation between wage inflation and current unemployment in the extreme regimes and the increase in statistical significance of the coefficients of lagged unemployment in those same regimes — albeit insufficient to attain significance in the prolonged expansion regime, when u_t is low —, but both again conflicting in sign with Galí's prediction. Moreover, insofar as the coefficient estimates in the intermediate or middle phase regime are so different from those of the extreme regimes, evidence for non-linearity is also confirmed and reinforced.

Most importantly, the NKWPC remains empirically well defined only in the intermediate regime, the inverse relationship between wage inflation and contemporary cyclical unemployment breaking down in the lower and upper unemployment regimes, which one may associate with prolonged expansions and recessions, respectively. While its poor fit during recessions may be attributed to the small sample size — $T = 35$ only, i.e, 16% of the sample —, a similar argument cannot be used with the observations of the most positive business cycle phase, as these represent more than 50% of the sample. A threshold type, nonlinear NKWPC, appears to fall short of explaining the recent upward nominal wage rigidity.

4 Concluding remarks

Our three-regime threshold regression model confirms and reinforces previous evidence for the non-linearity of the NKWPC. However, non-linearity alone appears insufficient to reconcile New Keynesian theory with recent data on anemic wage growth in the U.S. . Taking endogeneity issues into consideration strengthens the evidence for non-linearity but it also exposes more clearly the shortcomings of the Phillips curve as a successful description of wage dynamics in both extreme phases of the business cycle, when unemployment is either low or high. It appears that in those cases price indexation becomes weaker and, most importantly, the curve becomes completely flat, thereby losing its major (and defining) character.

Maybe this reflects the success of monetary authorities to fight inflation during prolonged expansions and to curb unemployment in recession periods, as McLeay and Tenreyro (2018) would argue. While our results agree with this hypothesis, further research is needed to validate it.

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