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Abhandlungen

Evaluating Phillips Curve Based Inflation Forecasts in Europe: A Note

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I. Introduction

The Phillips curve was established by *Phillips* (1958) as an empirical relationship between unemployment and nominal wage growth rate. Additional research led to the development of the modified Phillips curve showing the relationship between unemployment rate and inflation rate. *Friedman* (1968) added the natural rate of unemployment, thus establishing the NAIRU Phillips curve. More recent developments refine the theory by adding a system of stochastic price shocks, where the new macroeconomic price level is determined by, basically, discounted marginal costs and is only obtained at a given probability. This model framework is known as "New Keynesian Phillips curve", *Galí/Gertler* (1999) provide a thorough overview.

Empirical research on the topic has been twofold:

- The first branch of research emphasizes *model fit*, i.e. questioning whether the model is a good proxy for the data observed in the real world. *Paloviita* (2008) checks the model fit of several specifications using European data. *Blinder* (1997) pointed out already that the Phillips curve is known to apply rather badly there. Most recently, *Koop/Onorante* (2012) challenge estimating the Phillips curve in the anxious times of the financial crisis.
- The second branch of research focuses on *forecasting power*. The Phillips curve has been used as a tool for inflation rate forecasting. However, many studies find that the Phillips curve's usefulness as a forecasting tool is limited. For example, *Atkeson/Ohanian* (2001) find that Phillips curve based forecasters are regularly outperformed by simple persistence forecasters. *Matheson* (2008) gets a better forecasting performance out of a univariate AR(1) forecaster than from Phillips curve forecasting models. *Stock/Watson* (1999) use generalized Phillips curve forecasters and find mostly useful performances in a 12-months-fore-

casting horizon. *Stock/Watson* (2008) compare Phillips curve forecasters to several multivariate specifications of forecasting models and find a good Phillips curve performance for the US. However, *Clausen/Clausen* (2010) find that the Phillips curve performs badly oftentimes when analyzing data from Germany, the UK and the US.

In this paper we evaluate the NAIRU Phillips curve with adaptive expectations and compare their forecasting performance to the persistence benchmark forecaster suggested by *Atkeson/Ohanian* (2001). While their study focuses on the US we examine 15 euro-zone countries as well as the Euro area on average from 2001 to 2012 including a "pre-crisis" time frame and a period affected by the financial crisis starting in 2008. We show that the Phillips curve forecasters perform remarkably poor and are regularly outperformed compared to a naïve benchmark.

The paper is structured as follows: Section 2 provides an overview of the methodology used. Section 3 describes the data set. Section 4 presents the results and Section 5 concludes.

II. Phillips Curve Based Methods

This Section shortly describes the Phillips curve specification for forecasting, the reference forecaster and the applied methodology regarding result comparison.

1. Phillips Curve Specification

Phillips (1958) specified the empirical relationship between the nominal wage growth rate and unemployment either as a non-linear or log-linear relationship. Usually, a linearized version is applied focusing on the relationship between inflation rate π_t and the unemployment rate u_t. This so-called modified Phillips curve can be written as:

$$\pi_t = b u_t , \tag{1}$$

where b is a scaling parameter which is empirically found to be negative. Taking expectations with respect to the inflation rate $\left(E_{t-1}\left[\pi_t\right]\right)$ and integrating the difference between the actual unemployment rate and the non-accelerating inflation rate of unemployment $\overline{u}$ (i.e. the unemployment rate at which inflation rate does not change), a common specification is given by:

$$\pi_t - E_{t-1}\left[\pi_t\right] = b\left(u_t - \overline{u}\right). \tag{2}$$

Since expectations usually cannot be observed, the model is simplified by the assumption of adaptive expectations, i.e. it is assumed that agents form their expectations exclusively based on previous inflations rates:[1]

$$E_{t-1}[\pi_t] = \pi_{t-1}. \tag{3}$$

Therefore, the model can be rewritten as

$$\pi_t = a\pi_{t-1} + b(u_t - \bar{u}). \tag{4}$$

Since $-b\bar{u}$ is constant over time[2] this term can be separated to obtain

$$\pi_t = -b\bar{u} + a\pi_{t-1} + bu_t \tag{5}$$

or, in a notation for a linear regression model,

$$\pi_t = \beta_1 + \beta_2\pi_{t-1} + \beta_3 u_t + \varepsilon_t, \tag{6}$$

where ε_t is assumed white noise. Shifting Equation (6) one period ahead, this model results in the following forecasting equation:[3]

$$\pi_{t+1} = \beta_1 + \beta_2\pi_t + \beta_3 u_{t+1} + \varepsilon_{t+1}. \tag{7}$$

Equations (6) and (7) collapse to a random walk type stochastic process in case that β_2 does not differ significantly from one and both β_1 and β_3 do not differ significantly from zero. In that case, the Phillips curve model does not predict inflation rates more accurately than a pure random process. Thus, we test for that in Section 4 using these formal hypotheses:

$$H_0^A: \beta_1 = 0 \wedge \beta_3 = 0 \quad \text{vs.} \quad H_1^A: \neg H_0^A \tag{8}$$

and

$$H_0^B: \beta_2 = 1 \quad \text{vs.} \quad H_1^B: \neg H_0^B. \tag{9}$$

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[1] However, as a robustness check we also ran a model that incorporates expectations regarding the ECB inflation target that is "close to but below 2 %", i.e. we assumed static expectations. As to be foreseen, Phillips curve forecasts are very bad in that specification, so the results are omitted here but available upon request.

[2] Yet there is literature that suggests a time-varying NAIRU, e.g. Gordon (1997).

[3] Note that u_{t+1} itself must be forecasted. We use a univariate autoregressive method, i.e. $u_{t+1} = \alpha_1 + \alpha_2 u_t + \alpha_3 u_{t-1} + \nu_t$. This AR(2) approach is suggested as a simple plug-in method by the unemployment rate forecasting literature, e.g. Parker and Rothman (1998).

2. Reference Forecaster

Atkeson/Ohanian (2001) compare Phillips curve forecasts to naïve benchmark forecasts usually called "persistence":

$$\pi_{t+1} = \pi_t \tag{10}$$

Furthermore, *Atkeson/Ohanian* (2001, p. 3) point out that they use this as a reference "… *not because we think that it is the best forecast of inflation available, but rather because we think that any inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecasts are no more accurate than such a simple atheoretical forecast.*"

3. Result Comparison

Comparing two models' forecasting power is usually done in two steps: In the first step, both models are calculated pseudo-out-of-sample, i.e. by using a sub-sample for fitting and then calculating forecasts for another sub-sample period. In the second step, these forecasts are compared to actual realizations in that time frame. The difference between actual values and forecasted values is the forecasting error, e_t. We aggregate these errors by:

$$MAE = \sum_{t=1}^{m} |e_t|, \tag{11}$$

$$MSE = \sum_{t=1}^{m} e_t^2 \quad \text{and} \tag{12}$$

$$RMSE = \sqrt{MSE}, \tag{13}$$

where m is the number of forecasting errors.[4]

[4] MAE = Mean Absolute Error, MSE = Mean Squared Error, RMSE = Root Mean Squared Error.

III. The Data Set

We use monthly inflation rates and unemployment rates from January 2001 to August 2012 for Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia and Spain.[5] Furthermore, we employ aggregated data for the euro-zone.[6] As an inflation rate measure we chose both the original Harmonized Index of Consumer Prices (HICP overall) and a core inflation measure, i.e. HICP without energy and unprocessed food (HICP core inflation). Additionally, we utilize seasonally adjusted unemployment rate data. All data have been acquired from the ECB's statistical data warehouse.[7] The data set consists of 140 monthly observations per country and variable.

Most of these time series (both inflation rates and unemployment rates) are clearly non-stationary according to ADF tests. While it is quite possible to transform the data into a stationary stage (first differences, demeaning, Hodrick-Prescott filter, …) this would change the model specification away from the plain Phillips curve model, so we knowingly accept non-stationarity.

IV. Empirical Findings

We run a linear regression of the model described in Equation (6) through the whole sample set for each country and for both the HICP overall index and HICP core inflation index. Results are presented in Tables 1 and 2. Hypothesis H_0^A is not rejected most of the times, at least at a 5 % level of significance. Exceptions are Finland, Slovenia and Slovakia for HICP overall and Finland, France, Netherlands, Slovenia, Slovakia and the aggregated euro-zone for HICP core inflation. Hypothesis H_0^B is rejected at a 5 % level for Germany, Spain, Finland, France, Italy, Luxembourg, The Netherlands, Portugal, Slovenia, Slovakia and the aggre-

[5] These are the so-called Euro-17 countries as of the year 2011 excluding Estonia and Malta which both do not report complete unemployment rate data during the investigated time frame.

[6] These are countries that use the Euro as their national currency. The set of countries in that group changed during the investigated time frame, e.g. Cyprus has been using the Euro since January 2008.

[7] Internet source for HICP: http://sdw.ecb.europa.eu/browse.do?node=2120778 and unemployment rate: http://sdw.ecb.europa.eu/browse.do?node=2120805.

gated euro-zone for HICP overall and Germany, France, The Netherlands, Portugal, Slovenia, Slovakia and the aggregated euro-zone for HICP core inflation.

The Phillips curve therefore empirically seems to collapse to a random walk for Austria, Belgium, Greece and Ireland. However, the coefficient of determination (R^2) is rather high for all countries and spans from 0.7457 for Cyprus to 0.9699 for Ireland using HICP overall index data. The adjusted coefficient of determination $(\bar{R}^2)$is comparably high. Both R^2 and $\bar{R}^2$ are slightly higher for HICP core inflation data in tendency. After all it can be retained that the Phillips curve represents a rather good quality of fit.

After running out-of-sample forecasts as described in Section II.3. by using a rolling window with a fixed size of 70 observations (i.e. "half" of the data set[8]) we obtain aggregated forecasting measures MAE, MSE and RMSE for both forecasters and both index data. Results are presented in Tables 3 and 4. The Tables also contain information with respect to the percentage at which the persistence forecaster returns more precise forecasts than the Phillips curve forecaster, denoted as "Δ%".

[8] This splits the sample into an in-sample part that spans from January 2001 to March 2007 in the first round (which roughly determines the pre-crisis area) and an out-of-sample part from April 2007 to August 2012 to calculate forecasts for. However, results are robust against other sample decomposition decisions, i.e. instead of 70/70 obs. we also ran 45/95 and 95/45 splits. Results were similar and are available upon request.

Table 1

Results Regression Fit (HICP Overall Index)

Country	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	p-Value for $\beta_2 = 1$	p-Value for $\beta_1 = 0 \wedge \beta_3 = 0$	R^2	$\overline{R}^2$
Austria	0.9264**	0.8955***	–0.1624**	0.0020	0.0054	0.8801	0.8784
Belgium	1.0689*	0.9158***	–0.1138	0.0089	0.0323	0.8791	0.8773
Cyprus	0.4149*	0.8606***	–0.0148	0.0016	0.0232	0.7457	0.7419
Finland	0.0543	0.9468***	0.0054	0.0922	0.2402	0.8975	0.8959
France	0.6307	0.9112***	–0.0518	0.0101	0.0536	0.8547	0.8526
Germany	0.2411	0.9093***	–0.0106	0.0114	0.0817	0.8332	0.8307
Greece	0.2998	0.9084***	0.0012	0.0102	0.0242	0.8443	0.8420
Ireland	0.3510**	0.9421***	–0.0294**	0.0086	0.0151	0.9699	0.9695
Italy	0.1526	0.9201***	0.0038	0.0164	0.0849	0.8567	0.8546
Luxembourg	0.1994	0.8996***	0.0186	0.0081	0.0530	0.8119	0.8091
The Netherlands	0.3607	0.9583***	–0.0630	0.1013	0.1439	0.9458	0.9450
Portugal	0.3545*	0.9490***	–0.0239	0.0464	0.0708	0.9234	0.9223
Slovenia	0.4683	0.9758***	–0.0527	0.2616	0.2769	0.9427	0.9418
Slovakia	–0.1052	0.9623***	0.0191	0.1419	0.3000	0.9401	0.9392
Spain	0.3945*	0.9164***	–0.0118	0.0127	0.0577	0.8848	0.8831
Euro	0.4292	0.9292***	–0.0316	0.0191	0.0694	0.8872	0.8855

Significance codes: * = 5 %, ** = 1 %, *** = 0.1 % level.

Table 2

Results Regression Fit (HICP Core Inflation Index)

Country	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	p-Value for $\beta_2 = 1$	p-Value for $\beta_1 = 0 \wedge \beta_3 = 0$	R^2	$\overline{R}^2$
Austria	0.4519	0.8926***	–0.0581	0.0099	0.0414	0.8503	0.8481
Belgium	0.5917	0.8555***	–0.0428	0.0055	0.0183	0.7973	0.7943
Cyprus	0.3103*	0.8686***	–0.0210	0.0015	0.0323	0.7804	0.7772
Finland	–0.5148*	0.9901***	0.0653**	0.6134	0.0120	0.9527	0.9520
France	–0.0599	0.9657***	0.0124	0.2551	0.3192	0.9065	0.9051
Germany	0.1362	0.9103***	–0.0029	0.0230	0.1262	0.8062	0.8033
Greece	0.7861**	0.8249***	–0.0226	0.0003	0.0007	0.8384	0.8360
Ireland	0.2735*	0.9562***	–0.0241*	0.0212	0.0390	0.9813	0.9810
Italy	0.2418	0.8283***	0.0164	0.0005	0.0037	0.6927	0.6881
Luxembourg	0.3804*	0.8575***	–0.0046	0.0030	0.0078	0.7463	0.7426
The Netherlands	–0.0436	0.9993***	0.0136	0.9739	0.6636	0.9717	0.9713
Portugal	0.3970*	0.9231***	–0.0233	0.0223	0.0761	0.9169	0.9156
Slovenia	0.2192	0.9891***	–0.0222	0.4450	0.4266	0.9761	0.9757
Slovakia	–0.1430	0.9747***	0.0167	0.1593	0.2574	0.9705	0.9701
Spain	0.5629**	0.8692***	–0.0181*	0.0031	0.0144	0.8921	0.8905
Euro	0.0480	0.9591***	0.0025	0.2080	0.3165	0.9034	0.9020

Significance codes: * = 5 %, ** = 1 %, *** = 0.1 % level.

Table 3

Forecasting Results (HICP overall Index)

Country	MSE Phillips	MSE Persistence	Δ% MSE	MAE Phillips	MAE Persistence	Δ% MAE	RMSE Phillips	RMSE Persistence	Δ% RMSE
Austria	0.1447	0.1171	23.5520	0.2965	0.2600	14.0486	0.3804	0.3423	11.1539
Belgium	0.3472	0.2584	34.3424	0.4434	0.3786	17.1192	0.5892	0.5084	15.9062
Cyprus	0.5223	0.3849	35.7118	0.5874	0.4743	23.8531	0.7227	0.6204	16.4954
Finland	0.1941	0.1531	26.7645	0.3196	0.2771	15.3024	0.4406	0.3913	12.5897
France	0.1488	0.0949	56.8555	0.3121	0.2314	34.8646	0.3857	0.3080	25.2420
Germany	0.1616	0.1284	25.8574	0.3060	0.2729	12.1414	0.4020	0.3584	12.1862
Greece	0.3598	0.2150	67.3665	0.4897	0.3329	47.1162	0.5999	0.4637	29.3702
Ireland	0.3974	0.1540	158.0583	0.4742	0.3029	56.5792	0.6304	0.3924	60.6419
Italy	0.1626	0.1254	29.6046	0.2994	0.2486	20.4366	0.4032	0.3542	13.8440
Luxembourg	0.4416	0.3700	19.3502	0.4995	0.4400	13.5196	0.6645	0.6083	9.2575
The Netherlands	0.1436	0.1180	21.7320	0.2657	0.2314	14.8007	0.3790	0.3435	10.3322
Portugal	0.3408	0.1680	102.8605	0.4535	0.3143	44.3028	0.5838	0.4099	42.4291
Slovenia	0.4484	0.3549	26.3685	0.5376	0.4686	14.7346	0.6696	0.5957	12.4137
Slovakia	0.2135	0.1736	22.9795	0.3482	0.2786	24.9852	0.4620	0.4166	10.8961
Spain	0.3987	0.2627	51.7528	0.4471	0.3557	25.6925	0.6314	0.5126	23.1880
Euro	0.1330	0.0917	44.9918	0.2771	0.2057	34.7110	0.3647	0.3028	20.4125

$\Delta\%\,MSE = \left(\frac{MSE_{Phillips}}{MSE_{Persistence}} - 1\right) \cdot 100$, for MAE and RMSE analogously.

Table 4

Forecasting Results (HICP Core Inflation Index)

Country	MSE Phillips	MSE Persistence	Δ% MSE	MAE Phillips	MAE Persistence	Δ% MAE	RMSE Phillips	RMSE Persistence	Δ% RMSE
Austria	0.0478	0.0460	3.9015	0.1774	0.1686	5.2624	0.2186	0.2145	1.9321
Belgium	0.0493	0.0526	–6.1686	0.1770	0.1771	–0.0768	0.2221	0.2293	–3.1334
Cyprus	0.1749	0.1491	17.2373	0.3236	0.2914	11.0392	0.4182	0.3862	8.2762
Finland	0.0880	0.0609	44.5479	0.2159	0.1629	32.5957	0.2966	0.2467	20.2281
France	0.0271	0.0207	30.9792	0.1341	0.1129	18.8005	0.1647	0.1439	14.4462
Germany	0.0534	0.0477	12.0028	0.1714	0.1514	13.1872	0.2312	0.2184	5.8314
Greece	0.2356	0.1763	33.6234	0.3879	0.2914	33.0882	0.4853	0.4199	15.5956
Ireland	0.2740	0.1300	110.7972	0.3913	0.2657	47.2473	0.5235	0.3606	45.1886
Italy	0.1190	0.1177	1.1120	0.2387	0.2286	4.4523	0.3450	0.3431	0.5564
Luxembourg	0.0409	0.0377	8.3211	0.1599	0.1457	9.7034	0.2021	0.1942	4.0774
The Netherlands	0.0579	0.0477	21.2872	0.1733	0.1600	8.2952	0.2406	0.2184	10.1305
Portugal	0.1720	0.1094	57.1949	0.2994	0.2514	19.0649	0.4147	0.3308	25.3774
Slovenia	0.2108	0.1491	41.3442	0.3702	0.3200	15.6958	0.4591	0.3862	18.8882
Slovakia	0.1102	0.0626	76.1059	0.2714	0.1971	37.6621	0.3320	0.2501	32.7049
Spain	0.1897	0.1657	14.4699	0.2937	0.2400	22.3805	0.4355	0.4071	6.9906
Euro	0.0312	0.0253	23.2627	0.1399	0.1100	27.1826	0.1765	0.1590	11.0238

$\Delta\%\,MSE = \left(\frac{MSE_{Phillips}}{MSE_{Persistence}} - 1\right) \cdot 100$, for MAE and RMSE analogously.

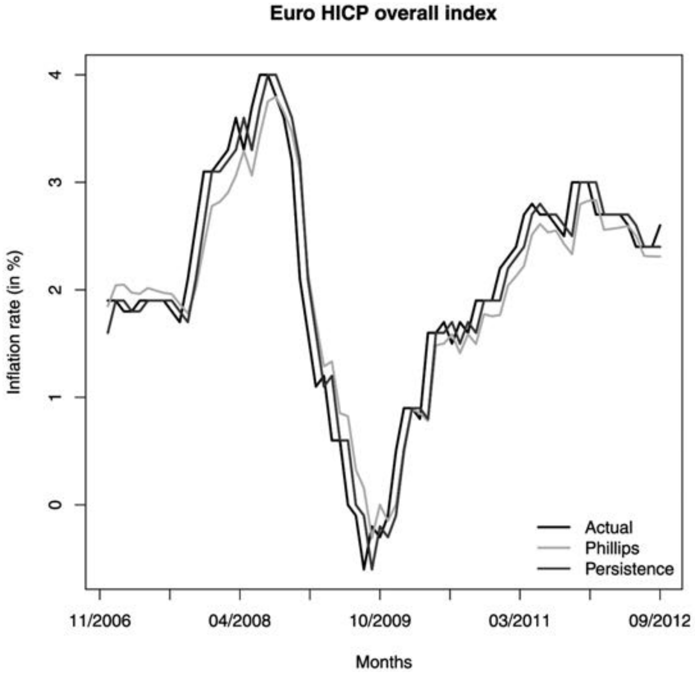

Figure 1: Euro Overall Inflation – Actual vs. Forecasted

With respect to the HICP overall index data this measure is always positive, indicating that the Phillips curve did not return a better forecast than the reference forecaster in any case. For the case of HICP core inflation index data this indicator is negative only for Belgium (for MAE, MSE and RMSE). However, the magnitude is comparatively small and Belgium is one of the few countries for which the empirical fit even collapses to a random walk. Figure (1) gives an example of the way typical actual-vs.-forecasted plots look like.[9] As Figure (2) shows, Belgium looks similar.

According to Chow breakpoint tests there are structural breaks in the model for several countries (e.g. for Greece, see Figure (3)) during the rolling window time frame. However, these breaks are significant for few countries only, many countries do not show significant structural breaks,

[9] It should be mentioned that the reference forecaster is by definition identical to the lagged actual values. The rest of the 30 plots have been omitted to conserve space and are available from the authors upon request.

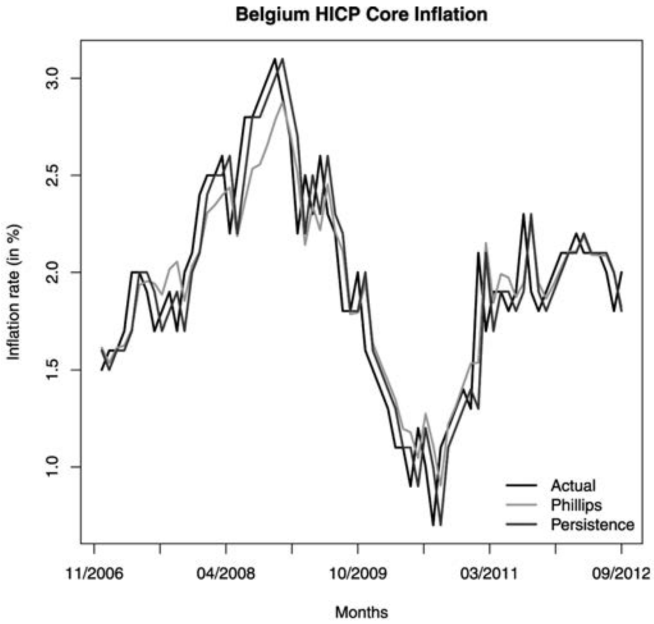

Figure 2: Belgium Core Inflation – Actual vs. Forecasted

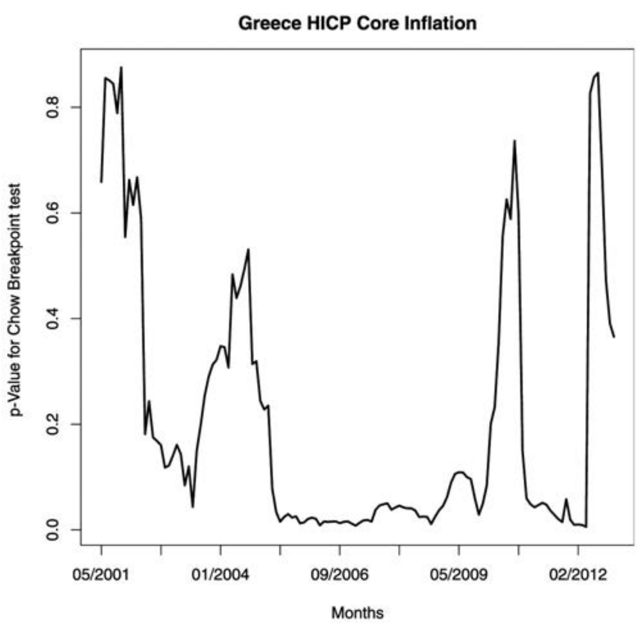

Figure 3: p-Values for Chow Breakpoint Test Over Time – Greece

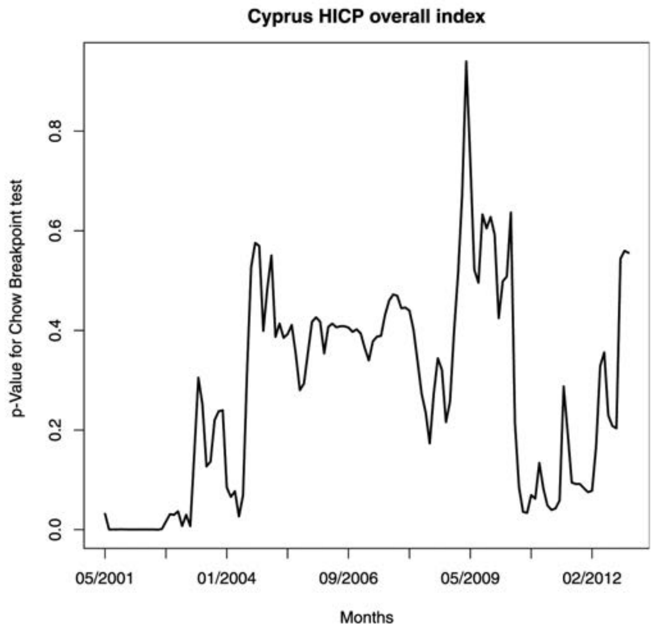

Figure 4: p-Values for Chow Breakpoint Test Over Time – Cyprus

at least not during the rolling window cycle (e.g. for Cyprus, see Figure (4)). After all, even though we strictly examine the Phillips curve model the data suggests to incorporate a breakpoint robust model instead. This is something professional forecasters should keep in mind.

V. Conclusion

In this paper we run out-of-sample forecasts for the inflation rates in 15 euro-zone countries and the aggregated euro-zone. We use HICP overall and HICP core inflation index data and compute the MAE, the MSE and the RMSE for a forecaster based on the NAIRU Phillips curve with adaptive expectations as well as for a naïve benchmark forecaster. We provide evidence that the Phillips curves' goodness of fit is rather high. However, forecasting power is comparatively low. Only Belgium returns smaller aggregated forecasting error measures for Phillips curve forecasts rather than persistence forecasts, but only for the HICP core inflation index data. Additionally, their numerical magnitude is rather small. In all other cases Phillips curve forecasting errors are much higher than those from the reference forecaster, in some cases even more than twice as high. This suggests that policy makers should not rely on Phillips curve based forecasting methods for euro-zone countries.

Stock/Watson (1999) conclude that Phillips curve can be a useful forecaster in the US. This is in line with *Blinder* (1997), who argues that the Phillips curve is an important tool in the US, admitting that it looks differently in other regions. *Atkeson/Ohanian* (2001, p. 7) however conclude more strongly, stating that "… *the search for yet another Phillips curve based forecasting model should be abandoned*". This paper's results suggest to agree.

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Summary

Evaluating Phillips Curve Based Inflation Forecasts in Europe: A Note

We run out-of-sample forecasts for the inflation rate of 15 euro-zone countries using a NAIRU Phillips curve and a naïve reference model. Comparisons show that the naïve model returns better forecasts in almost all cases. We provide evidence that the Phillips curves' goodness of fit is rather high. However, forecasting power is comparatively low. (C53, E31, E37)

Zusammenfassung

Bewertung von Phillipskurven-basierten Inflationsprognosen in Europa

In diesem Papier stellen wir Out-Of-Sample-Prognosen der Inflationsraten von 15 Ländern der Eurozone an. Hierzu verwenden wir einerseits ein NAIRU-Phillipskurven-Modell, andererseits ein naives Referenzmodell. Der Vergleich zeigt, dass das naive Modell in fast allen Fällen bessere Prognosen liefert als das Phillips-Modell. Obwohl die In-Sample-Anpassungsgüte des Phillips-Modells verhältnismäßig hoch ist, lässt sich somit folgern, dass die Prognosegüte der Phillipskurve vergleichsweise schlecht ausfällt. (C53, E31, E37)