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Inflation Dynamics and the Hybrid New Keynesian Phillips Curve: The Case of Chile

Abstract

It is recognized that the understanding and accurate forecasts of key macroeconomic variables are fundamental for the success of any economic policy. In the case of monetary policy, many efforts have been made toward understanding the relation between past and expected values of inflation, resulting in the so-called hybrid New Keynesian Phillips curve (HNKPC). In this article I investigate to which extent the HNKPC help to explain inflation dynamics as well as its out-of- sample forecast for the case of the Chilean economy. The results show that the forward-looking component is significant and accounts from 1.58 to 0.40 times the lagged inflation coefficient. Also, I find predictive gains close to 45% (respect to a backward-looking specification) and up to 80% (respect to the random walk) when forecasting at 12-months ahead. The output gap building process plays a key role delivering better

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results than similar benchmark. None of the two openness measures used—real exchange rate nor oil price— are significant in the reduced form. A final estimation using the annual variation of a monthly indicator of GDP deliver reasonable forecast accuracy but not as good as the preferred forecast-implied output gap measure.

Keywords: New Keynesian Phillips curve, inflation forecast, out-of-sample comparisons, survey data, real-time dataset.

JEL classification: C22, C53, E31, E37, E47.

1. INTRODUCTION

The aim of this article is to investigate to which extent forward-looking (FL) measures of inflation help to explain inflation dynamics as well as its out-of-sample behavior with a Phillips curve ensemble. This objective is tackled by analyzing the performance of the so-called hybrid New-Keynesian Phillips curve (HNKPC), introduced by Galí and Gertler (1999, GG), using a dataset of the Chilean economy.

It is widely recognized that the understanding and accurate forecasts of key macroeconomic variables are fundamental for the success in almost all economic policies. In the case of monetary policy, inflation forecasts are not useful from a practical but from a theoretical viewpoint also. Many efforts have been made toward understanding the relation between past and expected values of inflation (even going beyond the particular case of inflation; see Elliott, Granger, and Timmermann, 2006, and Clements and Hendry, 2011). The former component of inflation reflects the traditional inertia of price setting, while the latter stands as an ingredient of rational expectations agents' behavior. This corresponds to a confluence of the traditional Muth (1961) argument on asset dynamics but without allowing jumps given inertia modelling (Fuhrer, 2011). The HNKPC offers an amalgamation of these two components by allowing both a Calvo price setting scheme plus a fraction of FL price-setters firms (see Calvo, 1983, and GG).

Suppose a staggered price-setting scheme. Let $1-\theta$ the fraction of firms that change prices at a given period, and $1-\omega$ the fraction of firms that set prices optimally in a FL manner. Hence, current prices constitute a weighted average between backward- (BL) and FL-firms, leading to the HNKPC baseline equation:

$$\pi_t = \lambda x_t + \gamma_b \pi_{t-1} + \gamma_f \mathbb{E}_t\left[\pi^f_{t,t+h}\right] + \varepsilon_t \,, \tag{1}$$

where π_t is inflation, $\mathbb{E}_t\left[\pi^f_{t,t+h}\right]$ is the inflation expectation at period f, measured with a forecast made h-step ahead at period t, and x_t is a real marginal cost measure. $\left\{\lambda;\gamma_b;\gamma_f;\sigma^2_\varepsilon\right\}$ are parameters to be estimated, and ε_t is a cost-push shock, $\varepsilon_t \sim iid\ N\left(0,\sigma^2_\varepsilon\right)$. This specification constitutes a reduced form of a structural NKPC with $\gamma_f = \beta\theta/\phi$, $\gamma_b = \omega/\phi$, $\lambda = \left[(1-\omega)(1-\theta)(1-\beta\theta)\right]/\phi$ where β is a discount rate, and $\phi = \theta + \omega\left[1-\theta\left(1-\beta\right)\right]$. Equation 1 results in a convenient form as it allows many price setting schemes, making possible simple forecasting exercises (as, for instance, that of Jean-Baptiste, 2012).

There is a huge literature concerning a formal theoretical derivation of the HNKPC. Some examples are Smets and Wouters (2003, 2005), Christiano, Eichembaum, and Evans (2005), Erceg and Levin (2003), and Collard and Dellas (2004), among others.

Some other specifications, specially defined for open economies, include different and more complicated output gap definitions or simply more independent variables in Equation 1.[1] Galí and Monacelli (2005) analyze the case of the NKPC in a small open economy using a rich economic model leading to a simple reduced model including domestic inflation and output gap. There is also provided an application to the Canadian case; same as in Kichian and Rumler (2014). In the same

[1] A thorough review in this matter can be found in Corsetti, Dedola, and Leduc (2010).

vein (NKPC in small open economies), Rumler and Valderrama (2010) analyze the case of Austria, Balakrishnan and López-Salido (2002), Batini, Jackson, and Nickell (2005), and Posch and Rumler (2015) of the United Kingdom (UK), Leith and Malley (2007) of G7 countries, Rumler (2007) of Euro Area countries, and Mihailov, Rumler, and Scharler (2011) of some OECD countries. All these articles put a special attention to test the existence of an open economy component and in some cases providing out-of-sample evidence. There is no a unique nor common way on how to include openness in the baseline model. It is expected to differ considerably on the manner how openness is included. But, openness in reduced form equation typically lies within the options of either the output gap or as an independent variable. Obviously, the latter type is easier to handle with forecasting purposes.

Many of the empirical evidence of the HNKPC have been collected for industrialized economies. Some selected examples are Roberts (1997), GG, Galí, Gertler, and López-Salido (2005), Rudd and Whelan (2005), and Brissimis and Magginas (2008) for Unites States (US), Jean-Baptiste (2012) for the UK, McAdam and Willman (2003) for the Euro Area, and Jondeau and Le Bihan (2005) for the UK and major Euro Area countries. The main difference in their methodology concerns inflation expectation proxies, real-time estimates with different data vintages, and the measurement of marginal costs.[2]

A current controversial methodological discussion confronts the results obtained by Rudd and Whelan (2005) in opposition to those of GG. While the former finds that lagged inflation is the major driver of current inflation, the latter states that is the FL component. This bifurcation is due to different

[2] It is worth mentioning that the US economy has richer conclusions on this matter as it has several sources of survey expectations data with a long sample span, as is the case of the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia, the Livingstone Survey, the Michigan Survey, the Greenbook, Consensus Forecasts, the Congressional Budget Office, and the Real-Time Data Set for Macroeconomists (Croushore and Stark, 2001).

specifications and estimation method assumptions; still an ongoing buoyant discussion. This article follows more closely the GG derivation of the HNKPC, with some minor twists explained later. Closer literature supporting the GG findings and methodology are Galí, Gertler, and López-Salido (2001), Sbordone (2002), Smets and Wouters (2003, 2007), Levin et al. (2005), Rabanal and Rubio (2005), Nason and Smith (2008) –using the SPF expectations for the US economy–, and Henzel and Wollmershauser (2008) –using CESifo World Economic Survey for Italy– among others.[3]

More evidence on the HNKPC is provided by Paloviita and Mayes (2005) for a panel of OECD countries. The authors, by using a real-time database, find an influential role for the expectations; also unveiling the controversial role of the output gap as a measure of marginal costs. Also considering real-time data, Gruen, Robinson, and Stone (2002) and Robinson, Stone, and van Zyl (2003) consider the case of Australia. The issue of real-time datasets has been analyzed thoroughly in Orphanides (2001), Orphanides and van Norden (2002, 2003), and Rünstler (2002). They provide evidence supporting the view that due to different data vintages, estimated coefficients are subject to a substantial data measurement uncertainty.

Canova (2007) analyzes the case for G7 countries using several multivariate economics and statistical-based models. Nunes (2010) analyze the case for United States, whether is allowed rational expectations and expectations coming from a survey. By doing this, the author is able to include different types of firms when setting prices beyond the traditional Calvo setup. Granger and Jeon (2011) reinterpret the original Phillips (1958) article with modern econometric techniques using the original and extended data sample for the UK. This exercise is

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[3] There is also literature supporting the Rudd and Whelan (2005) arguments –specially concerning the theoretical derivation of the NKPC– as, for instance, Rudd and Whelan (2007), Agénor and Bayraktar (2010), Mazumder (2010, 2011), Abbas and Sgro (2011), Lawless and Whelan (2011), and Vašíček (2011).

interesting since ease a comparison with all the new elements developed to obtain the GG NKPC.

Some other approaches include that of Carriero (2008) arguing that it is possible to test the NKPC without having to estimate its structural parameters. Using this approach, the author is unable to find a combination of structural parameters coherent with US data. This result suggests that the process of expectations formation does not necessarily obeys entirely to the rational expectations hypothesis. Lanne and Luoto (2013) propose an estimation method based on a univariate noncausal autoregressive model to avoid simultaneity problems when using the GMM estimators. By using this, most of the quarterly US inflation dynamics seems driven by inertia. Some other variations can be found in Smets and Wouters (2002), Matheron and Maury (2004), Batini, Jackson, and Malley (2005), Petrella and Santoro (2012), Malikane and Mokoka (2014), and Posch and Rumler (2015), among others.

Finally, for the case of Chile, little research has been conducted in this matter. Some exceptions are Céspedes, Ochoa, and Soto (2007) and Pincheira and Rubio (2010). The first article derives a NKPC from a structural microfounded model, and analyzes their in-sample ability to explain inflation dynamics. The second article addresses the issue of the weak predictive power of purely BL PC with real-time data. While Céspedes, Ochoa, and Soto (2007) also provide an out-of-sample assessment, it is not the major concern of the authors. Instead, inner motivation of Pincheira and Rubio (2010) –shaping the specification search exercise– is precisely forecast accuracy.

In this article I first estimate an unrestricted version of the HNKPC with Chilean data, to then compare its predictive power with a BL PC and traditional benchmarks predicting at h-months-ahead, $h = \{1; 3; 6; 12\}$. The dataset corresponds to monthly inflation, a monthly index of economic activity, and the expectations of the Chilean Survey of Professional Forecasters (ChSPF). The estimation is made through the generalized method of moments (GMM). As a robustness exercise, I also analyze to what extent traditional openness measures are allowed in the reduced form of Equation 1. Again, for robustness purposes, I conduct the same estimations with the so-called *core inflation*. A stability analysis is complemented with some recursive estimations to shed some light about (in-sample) parameter uncertainty.

The results show that the FL inflationary component is statistically significant when is included in the specification. In size, accounts from 1.58 to 0.40 times the lagged inflation coefficient. Real-time ChSPF forecasts of output are also useful but as instruments.[4] When considering short-term forecasting, I find predictive gains close to 45% (respect to the BL specification) and up to 80% (respect to the random walk) when forecasting at 12-months-ahead. However, these gains are not statistically significant according to the traditional Giacomini and White (2006; GW) test. In sum, these results should be read carefully and just as a valid benchmark.

The in-sample results for core inflation support the existence of the HNKPC. Nevertheless, predictive results suggest that core could be a process with higher memory. The output gap plays a key role delivering better results than similar benchmark. None of the two openness measures used –real exchange rate nor oil price– deliver significant results in the reduced form. A robustness checking estimation using the annual variation of a monthly indicator of GDP instead of output gap deliver reasonable forecast accuracy but not as good as the preferred forecast-implied output gap measure.

The article proceeds as follows. In Section 2, I detail the econometric procedure, alongside the dataset utilized emphasizing the output gap construction –an unobservable variable. Section 3 presents the empirical results divided in those obtained in-sample and those when predicting both measures of inflation. It is also presented the result of robustness exercises. Finally, Section 4 concludes.

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[4] This finding is in line with those of Orphanides and van Norden (2002, 2005) obtained for the US economy.

2. ECONOMETRIC SETUP

The baseline specification is the Equation 1. To avoid part of the simultaneity in the variables of the right hand side, I estimate Equation 1 with GMM. However, this method eliminates *methodological* simultaneity only, as the series exhibits a high correlation given their underlying data generating process. I make use of lagged observations of the variables as instruments (IV), described and tested later. Recall that the problem that GMM addresses is the orthogonality condition $\mathbb{E}_t\left[\mathbf{x}_t' \varepsilon_t\right]$ that no longer holds. Hence, it is needed to instrumentalize the $\mathbf{x}_t'$ matrix with another one, say $\mathbf{z}_t$, containing ℓ IV $(\ell \geq k)$ which fulfils:

2 $$\mathbb{E}_{t-1}\left[\left(\pi_t - \lambda x_t + \gamma_b \pi_{t-1} + \gamma_f \mathbb{E}_t\left[\pi^f_{t,t+h}\right]\right) \times \mathbf{z}_{t-1}\right] = 0 \cdot$$

In this context, a formal test for IV suitability is analyzed through the Hansen's *J*-statistic:

3 $$J\left(\hat{\boldsymbol{\beta}}, \hat{\mathbf{w}}_T\right) = \frac{1}{T}\left(\pi_t - \mathbf{x}_t' \hat{\boldsymbol{\beta}}\right)' \mathbf{z}_t \, \hat{\mathbf{w}}_T^{-1} \, \mathbf{z}_t' \left(\pi_t - \mathbf{x}_t' \hat{\boldsymbol{\beta}}\right),$$

where $\hat{\mathbf{w}}_T$ is a $\ell \times \ell$ symmetric and positive-definite weighting matrix, as it weight the moments considered in the estimations. Hence, GMM finds the vector of coefficients:

4 $$\hat{\boldsymbol{\beta}} = \left(\mathbf{x}'\mathbf{z}\,\hat{\mathbf{w}}_T^{-1}\,\mathbf{z}'\mathbf{x}\right)^{-1} \mathbf{x}'\mathbf{z}\,\hat{\mathbf{w}}_T^{-1}\,\mathbf{z}'\mathbf{y},$$

that minimizes Equation 3. As $J\left(\hat{\boldsymbol{\beta}}, \hat{\mathbf{w}}_T\right) \sim \chi^2_{l-k}$, along with the estimated coefficients it is also reported the *p*-value that test the null hypothesis: $\mathbb{E}_T\left[J\left(\hat{\boldsymbol{\beta}}, \hat{\mathbf{w}}_T\right)\right] = 0$. If p-value $> \alpha$, the IV are valid at the α-level of significance.

The estimation of the weighting matrix is made according to Hansen (1982) recommendation –the inverse of covariance matrix, i.e. $\hat{\mathbf{w}}_T = \hat{\mathbf{s}}^{-1}$, and avoiding potential autocorrelation with the Newey-West HAC method. The estimation of both covariance matrices-for the two stages: IV and final regression –is set in the same manner. The whitening lag specification is set automatic, to be selected according the Bayesian Information Criterion (BIC) choosing in a maximum of three lags (following the rule $T^{1/3}$).

Despite the solution offered by the IV, some other problems could arise. A common setback is when IV are *weak instruments*. The problem could be easily explained when comparing the two available estimators –OLS $\left(\tilde{\boldsymbol{\beta}}\right)$ and GMM $\left(\hat{\boldsymbol{\beta}}\right)$: $\tilde{\boldsymbol{\beta}} = (\mathbf{x}'\mathbf{x})^{-1}\mathbf{x}'\mathbf{y}$ and $\hat{\boldsymbol{\beta}} = (\boldsymbol{\eta}'\mathbf{x})^{-1}\mathbf{x}'\mathbf{y}$ with $\boldsymbol{\eta} = \mathbf{z}\hat{\mathbf{w}}_T\mathbf{z}'$. So, the relative asymptotic bias could be expressed as:

$$\boxed{5}\ \text{Relative Asymptotic Bias} = \frac{\underset{T\to\infty}{\text{plim}}\left[\hat{\boldsymbol{\beta}}-\boldsymbol{\beta}\right]}{\underset{T\to\infty}{\text{plim}}\left[\tilde{\boldsymbol{\beta}}-\boldsymbol{\beta}\right]} = \frac{\mathbb{C}[\boldsymbol{\eta},\varepsilon]}{\mathbb{C}[\mathbf{x},\varepsilon]}\cdot\mathbb{C}[\boldsymbol{\eta},\mathbf{x}]^{-1}.$$

From Equation (5) it is easy to notice that the higher $\mathbb{C}[\boldsymbol{\eta},\mathbf{x}]$, the smaller the relative asymptotic bias. Note also that:

$$\boxed{6}\ \mathbb{V}\left[\hat{\boldsymbol{\beta}}\right] = \sigma_\varepsilon^2(\mathbf{x}'\boldsymbol{\eta})^{-1}(\boldsymbol{\eta}'\boldsymbol{\eta})(\boldsymbol{\eta}'\mathbf{x})^{-1}$$
$$= \sigma_\varepsilon^2\left(\mathbf{x}'\mathbf{x}\right)^{-1}(\mathbf{x}'\boldsymbol{\eta})^{-1}(\boldsymbol{\eta}'\boldsymbol{\eta})(\boldsymbol{\eta}'\mathbf{x})^{-1}\left(\mathbf{x}'\mathbf{x}\right) = \mathbb{V}\left[\tilde{\boldsymbol{\beta}}\right]\cdot\rho_{\eta\mathbf{x}}^{-2}.$$

Hence, the lower the correlation between $\mathbf{x}$ and $\boldsymbol{\eta}$ $\left(\rho_{\eta\mathbf{x}}\right)$, the higher the variance of the IV estimator relative to that of OLS. For the set of IV used in each estimation it is used the Stock and Yogo (2010) test, which null hypothesis is: *IV are weak*. Note that it is computed through the Cragg-Donald F-statistic. More details on the econometrics of weak instruments can be found in Bound, Jaeger, and Baker (1995), Stock, Wright, and Yogo (2002), and Moreira (2009). A deep overview for the specific case of the NKPC can be found in Nason and Smith (2008).

All the estimations are made through the GMM estimator. There are many reasons to prefer this method. First, and following GG, the GMM results are robust to the non linear IV GMM (NLIVGMM) estimator, which has been criticized by, for instance, Lindé (2005) and Rudd and Whelan (2005). This is a good reason to keep GMM since NLIVGMM estimation requires more computer time and it is more sensitive to the IV election in a univariate ensemble. Hence, GMM is more efficient in the sense that Chumacero (2001) suggests, and it has proved to be as good as NLIVGMM when accommodating eventual specification bias.[5]

Second, GMM is also the preferred estimation method in several articles that follow GG especially with forecasting purposes. This is the case of Brissimis and Magginas (2008), Rumler and Valderrama (2010), Jean-Baptiste (2012), Kichian and Rumler (2014), and Posch and Rumler (2015) among others. It is often argued that the use of this estimator must be strongly attached to IV validation through Hansen's test and weak instruments results. Both elements are empirically analyzed later.

Finally, there is no a clear nor widely accepted reason to use an estimator different to GMM. GG response to Lindé (2005) proposal towards full information maximum likelihood (FIML) estimator relies heavily on a supposedly flaw simulation exercise.[6] As emphasized by Cochrane (2001), the election between one (GMM) or another (ML) estimator for univariate cases is a trade-off, and no consensus has been achieved. So, choosing GMM implies more sensitivity to IV selection but reducing misspecification risk to false assumptions made for the error term.

2.1 Data

Equation 1 involves three different kinds of series: actual inflation, inflation expectations, and the output gap. The source of all variables is the Central Bank of Chile (CBC). The available sample spans from 2000m1 to 2013m12 (168 observations).

5 An assessment of criticism response can be found in subsection 1.2 of GG.

6 In particular, GG states in regard of the use of FIML: "[...] While we do not take a stand on this claim we find Lindé's argument unconvincing. In particular as we discuss below Lindé's Monte Carlo exercise is heavily tilted in favor of FIML." (p. 1110).

When forecasting, it is used the firsts 77 observations (2000m1-2006m5) as *estimation sample*, leaving the remaining 91 observations to *evaluation sample* (2006m6-2013m12). This scheme delivers 91 out-of-sample observations when predicting one-step ahead, 89 for 3-, 86 for 6-, and 80 for 12-months ahead.

Actual inflation –*headline inflation*– corresponds to annual percentage change of the total CPI (index level, 2013 = 100), the same measuring units in which the inflation target is set. For robustness exercises, I make use of another inflation measure, the so-called *core inflation*. This corresponds to the CPI inflation but extracting the components of *Food and beverages* and *Energy* (reducing exogenous volatility).

The inflation expectations are provided by the ChSPF.[7] The ChSPF is informed at the beginning of each month. Inflation forecasts are delivered for 1-, 12-, and 24-months ahead, along with projections of GDP for the current and following year. It collects answers from academics, consultants, executives and private sector consultants who also report forecasts for other variables. Since each individual analyst's projections are not revealed, the median forecast is used. The ChSPF starts in 2000 and several times has changed its content. Except for minor changes made since 2004m11, it has remained unaltered. On average over the period 2000-2009, 35 analysts completed the questionnaire each month.

Note that another source of inflation expectations is the Consensus Forecasts monthly report. However, the expectations provided there are made in a fixed-horizon basis. This is, every month it is reported the forecast for December of the current and next year. Hence, the information provided for intermediate horizons would be weaker than that coming from a moving horizon forecast. Moreover, this will redound into an inefficient forecast since the implied errors will show smaller errors at longer horizons that those made at shorter horizons.

[7] Database freely available at <http://www.bcentral.cl/eng/economic-statistics/series-indicators/index_ee.htm>. See Pedersen (2010) for details.

Table 1

DESCRIPTIVE STATISTICS OF USED TIME SERIES[1]

	Symbol (stationary)	*Mean*	*Median*	*Standard deviation*	*Max.*	*Min.*	*ADF statistic[2] (level)*	*ADF statistic (annual var.)*
Inflation (headline)	π_t	3.18	2.96	2.17	9.85	−2.27	−0.24 (0.930)	−2.59 (0.096)
Inflation (core)	$\tilde{\pi}_t$	2.32	2.22	1.42	7.00	−1.63	−2.94 (0.154)	−4.06 (0.009)
EAMI	y_t	4.40	4.67	2.63	13.18	−4.43	−2.80 (0.199)	−3.04 (0.033)
ChSPF: inflation ($t+12$)	$\pi^f_{t,t+12}$	3.08	3.00	0.06	6.00	2.00	−3.99 (0.011)	
ChSPF: inflation ($t+24$)	$\pi^f_{t,t+24}$	3.07	3.00	0.17	3.90	2.60	−4.36 (0.003)	
ChSPF: EAMI ($t+1$)	-	4.17	4.50	2.08	13.00	−3.60	−2.74 (0.069)	
ChSPF: GDP (T)[3]	-	4.36	4.80	1.78	6.50	−1.80	−3.00 (0.037)	

ChSPF: GDP ($T+1$)	-	4.80	5.00	0.46	6.00	3.30	−2.72 (0.074)
Output gap Bwd	$\hat{y}_t$	−0.00	0.00	0.02	0.05	−0.06	−1.92 (0.053)
Output gap Fwd ($t+12$)	$\hat{y}^f_{t,t+12}$	−0.00	−0.00	0.02	0.07	−0.07	−2.83 (0.005)
Output gap Fwd ($t+24$)	$\hat{y}^f_{t,t+24}$	−0.04	−0.04	0.03	0.03	−0.09	−2.73 (0.072)
Real exchange rate	q_t	0.91	0.46	7.26	17.80	−15.57	−2.30 (0.021)
Oil price	p_t	19.97	14.51	36.52	170.88	−54.65	−4.92 (0.000)

Notes: [1]Sample: 2000m1-2013m12 (168 observations). [2]ADF stands for the augmented Dickey-Fuller unit root test. ADF p-value is shown in parenthesis. ADF computed with constant, trend [core, EAMI, ChSPF: inflation ($t+12$), ChSPF: inflation ($t+24$)], or none (output gap backward, output gap forward ($t+12$), real exchange rate, oil price). Bandwidth ranging from four to 24 lags. [3] t stands for monthly frequency, while T for annual.
Source: Author's elaboration.

Table 1 displays some descriptive statistics of all the series, including the output gap which is described in the next subsection. Basically, its construction relies on the use of the Economic Activity Monthly Index (EAMI, index level 2013 = 100), which constitutes a monthly measure of GDP.[8] Note that the preferred transformation to achieve stationary in level series is the annual percentage change. This transformation is preferred because it is achieved stationarity according to the Augmented Dickey-Fuller test it is an easy to interpret standard transformation, and matches the denomination of the ChSPF answers.

Finally, for robustness purposes, and considering this case as an open economy, there is also analyzed the real exchange rate and the Brent oil price (sources: CBC and Bloomberg) as independent stationary variables in Equation 1. Note that both headline and core inflation already include information from oil price, since there is a considerable pass-through to domestic prices (see De Gregorio, Landerretche, and Neilson 2007; and Pedersen, 2011, for details). In contrast, the real exchange rate considers a more genuine interaction dynamics between the domestic and foreign economies.

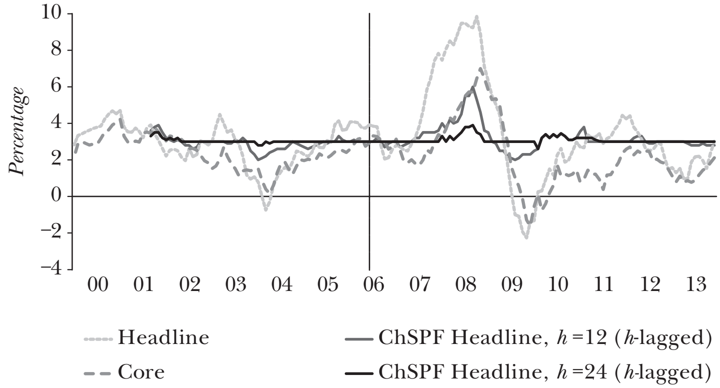
Figure 1 displays the actual and h-lagged forecasted inflation series across the whole sample. Note that the inflation expectation 24-months ahead [ChSPF: inflation ($t + 24$)] is very close to the inflation target the majority of the time. Also, the time span includes the global inflationary spillover of the recent financial crisis.

Note that the use of ChSPF dataset is made under a number of implicit assumptions. One of the most important is that respondents minimize their mean squared forecasted error, i.e. quadratic loss function. This implies, among other results, that they are efficient into incorporating and using new available information. For an appraisal of the suitability of these projections, in Figure 2, I plot the cross-correlation between inflation

[8] Moreover, the annual rate of growth of the EAMI coincides with that of the GDP for each third month of each quarter. EAMI as well as inflation are freely available at: <http://si3.bcentral.cl/Siete/secure/cuadros/arboles.aspx>.

Figure 1

ACTUAL AND *H*-LAGGED FORECASTED HEADLINE AND CORE INFLATION[1]



[1] Vertical line indicates out-of-sample forecasts start point (2006.6).
Source: Author's elaboration using CBC's dataset.

(both) and the ChSPF expectations for 12 and 24 months. After noticing that the forecast is made for headline inflation, both expectations variables match the horizon at which they are targeting relatively well. As expected, however, it is a less clear cut with core inflation. In that case it is observed that expectations match the horizon with almost three or four lags but with a similar accuracy.

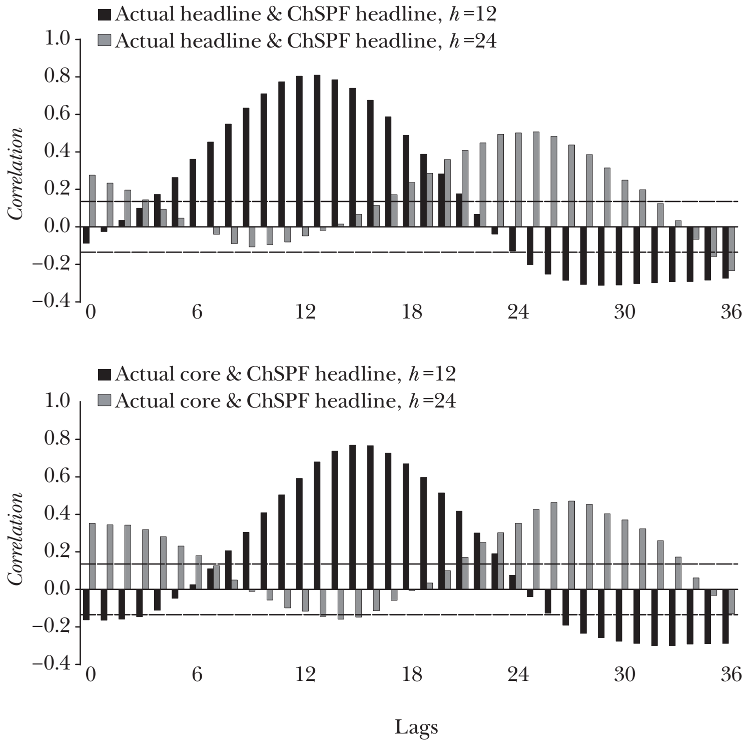
2.2 Output Gap Building Blocks

One of the major drawbacks when estimating the NKPC is the impossibility to accurately measure the excess of demand, i.e. marginal costs. The typical alternative is the output gap, i.e. the difference between the current and potential output.[9] Basically,

[9] Note that I focus on output gap instead of unemployment gap following the recommendations of Staiger, Stock, and Watson (1997a, 1997b).

Figure 2

CROSS-CORRELATION. INFLATION AND (LAGS OF) CHSPF EXPECTATIONS[1]



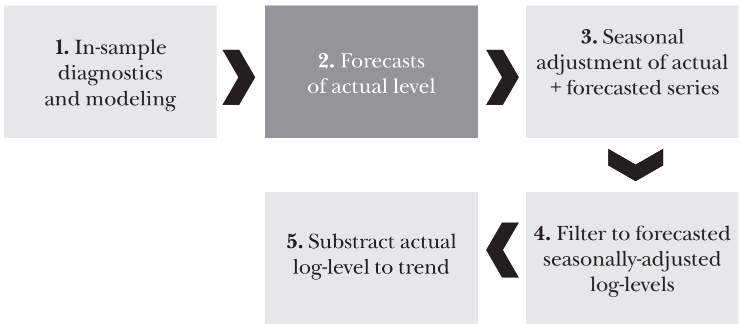
[1] Confidence interval: $0 \pm Z_{\alpha}/\sqrt{n}$, where α is the probability-level of the inverse normal distribution ($n = 168$) (see Chatfield, 2004, for details).
Source: Author's elaboration.

instability arise with the *end-of-sample* problem of filtering, especially when the Hodrick-Prescott (HP) procedure is used to obtain the potential output; an unobservable component.[10] To alleviate this setback, I follow the approach proposed by Bobbitt and Otto (1990) and Kaiser and Maravall (1999), relaunched by Mise, Kim, and Newbold (2005). This consists of

[10] See Orphanides (2001), Orphanides and van Norden (2002, 2005) and Garratt et al. (2008) for a discussion on this matter.

Figure 3

OUTPUT GAP BUILDING BLOCKS



Source: Author's elaboration.

adding forecasted observations to level series prior to perform any filtering procedure. Hence, the method applied to obtain the output gap follows the steps of Figure 3. Note that the seasonal adjustment is made with X-12-ARIMA in its default mode, and the filtering method is HP $(\lambda = 129{,}600)$.

As the method involves the use of forecasted observations, three measures of output gap emerges: *i)* using forecasted values up to five-years ahead (60 observations) coming from an ARMA(p, q) model (labelled: *Bwd*), *ii)* using ChSPF GDP forecast for the current year [*Fwd (t + 12)*], and *iii)* same as *ii)* but using forecast for the following year [*Fwd (t + 24)*]. As a result, three different matched specifications of the Equation 1 are analyzed:

1) a (now non-strictly) BL model, including lagged inflation only, plus *Bwd* output gap,

2) a FL model, including lagged inflation, the ChSPF expectations of inflation 12-months ahead, plus *Fwd (t + 12)* output gap, and

3) a FL model, including lagged inflation, the ChSPF expectations of inflation 24-months ahead, plus *Fwd (t + 24)* output gap.

The chosen ARMA model for EAMI corresponds to $\Delta^{12}Y_t = y_t = \alpha + \rho y_{t-1} + \theta_1 v_{t-1} + \theta_{12} v_{t-12} + v_t$, with $v_t \sim iid\ N\left(0, \sigma_v^2\right)$, chosen with the *general-to-specific* (GETS) iterative process allowing for skipped terms. The estimation is presented in Table 2, which also reveals robust results across the sample span, and a correct specification according to the Durbin-Watson statistic.

In Appendix A it is compared the stability across the sample of the purely BL and *Bwd* output gap measures to assess the stability gain using forecast observations. This procedure redounds into a more demanding BL benchmark for the HNKPC estimation and forecasts. As expected, the latter methodology exhibit minor deviations while the number of observation is increased.

Several articles use output gap as a proxy of marginal costs, differing often on the way how to obtain detrended output (whether based on HP or other device). The economic rationale behind this measure is striking; it considers the distance between the current state of the economy and the counterfactual that may be obtained if all factors were employed in the absence of shocks. Some examples using output gap are Rudebusch and Svensson (1999), Stock and Watson (1999), Lindé (2005), Paloviita and Mayes (2005), Rudd and Whelan (2005), Galí, Gertler, and López-Salido (2005), Canova (2007), Dees et al. (2009), Nunes (2010), and Jean-Baptiste (2012), among others. Moreover, Batini, Jackson, and Nickell (2005) use output gap alongside the labor share on the basis of an endogenously determined price mark-up.

Nevertheless, some other measures of marginal costs have been also used. In particular, GG and many other authors make use of the logarithm of the non-farm business labor income share. For the particular case of Chile, Pincheira and Rubio (2010) make use of the HP-based output gap, whereas Céspedes, Ochoa, and Soto (2007) of a more complicated specification relying heavily on structural assumptions (and ultimately

Table 2

AUXILIARY MODEL FOR EAMI (y_t) FORECASTS[1]

	Estimation sample	*Full sample*
Dep. variable	y_t	y_t
ρ	0.961 (0.000)	0.893 (0.000)
θ_1	−0.510 (0.000)	−0.226 (0.000)
θ_{12}	−0.489 (0.000)	−0.773 (0.000)
α	6.536 (0.000)	4.360 (0.000)
$\bar{R}^2$	0.656	0.741
D-W statistic	2.288	2.355
RMSE	1.209	1.324
Sample	2000m2-2006m5	2000m2-2013m12
Number of observations	76	167

Notes: [1] *p*-value shown in parenthesis. Variance corrected with Newey-West HAC. RMSE stands for root mean squared error.
Source: Author’s elaboration.

depending on calibrated parameters). Due to frequency considerations (monthly in this article versus quarterly in Céspedes, Ochoa, and Soto, 2007), I am unable to replicate their marginal cost measure. Also, some of the input data used to build their marginal cost measure has suffered of a major methodological change since 2010 making difficult a fair extension of the sample (see INE, 2010, for details).

Finally, Stock and Watson (1999) suggest that especially when the aim is to forecast, the output gap measure provides a convenient alternative since relies basically in a univariate ensemble. Also, some of the major problems associated with output gap –instead of using marginal cost– are rather an empirical issue. Typically is the *end-of-sample* problem, already tackled in this article in an *efficient* manner according to Chumacero (2001).

2.3 Out-of-sample Assessment

To investigate whether the BL or one of the two FL specifications is better at forecasting, I compute and compare the root mean square forecast error (RMSFE):

$$\text{RMSFE}_h = \left[\frac{1}{T} \sum_{t=1}^{T} \left(\pi_{t,t} - \pi_{t,t-h}^{f} \right)^2 \right]^{\frac{1}{2}}, \tag{7}$$

where $\pi_{t,t-h}^{f}$ is the forecast h-step-ahead of $\pi_{t,t}$, made at period t. For completeness, and a more demanding comparison, I also include two competing models: the random walk (RWK), and an AR(p) model choosing p according to a fixed-T version of the *stepwise backwards* procedure (labelled: AR[*SB*]). This last model, similar to GETS, chooses the autoregressive order p within the estimation sample, fixing it until the last observation is used for estimation. Note that OLS deliver misleading results (not shown), implying that each forecast involve the multistage estimation once an observation is added to the sample (and dropping the last one under a rolling window scheme).

Finally, statistical inference is carried out with the GW test of predictive ability. It requires that errors have to be computed in a rolling window scheme, and works for both nested and non-nested models. The null hypothesis can be summarized as *both models have the same predictive ability conditional to its model* (see Clark and McCracken (2013), for a comprehensive description of the test.)

2.4 Robustness Exercises

Despite that the baseline exercises (in- and out-of-sample) are reestimated using core inflation, three more estimations are conducted. As above mentioned, to analyze whether international variables play a role in inflation dynamics, there is included in Equation 1 the real exchange rate (q_t) and the oil price (p_t) separately. Hence, the equation to be estimated corresponds to:

$$\pi_t = \lambda x_t + \kappa g_t + \gamma_b \pi_{t-1} + \gamma_f \mathbb{E}_t \left[\pi^f_{t,t+h} \right] + \varepsilon_t , \quad (8)$$

where g_t is either q_t or p_t, and κ is a new parameter to be estimated. The remaining robustness exercise consists simply on the substitution of x_t as output gap and defining x_t as the annual percentage change of EAMI.

It is worth mentioning that all specifications, i.e. variables, lags, and IV, for the baseline close economy case were chosen following a t-statistic significant criterion in two sample spans: using the *estimation* sample and the *full* sample. Any specification that does not fulfil statistical significance within these two samples is discarded. If the specification fulfils the criterion, then it is analyzed its forecasting power and becoming the preferred specification. After having found the *preferred* specification it is analyzed the case with g_t variable, making use of the same lag and IV structure. Hence, analyzing simply the marginal information that g_t would provide.

3. RESULTS

3.1 In-sample Results

The results for the three specifications with headline are presented in Table 3 for two samples: *estimation* (1-5) and *full* sample (6-8). The J-stat. p-value indicates that IV are valid along the sample span except for the BL specification. The list of IV and its used lags is presented in Table 5. It also reports the weak instruments testing results. There are two other variables tested as IV: Consensus Forecasts' Brent oil price and ChSPF's foreign exchange rate. They both result as no valid IV with any acceptable lag length. Also, according to the Stock and Yogo (2010) test, the set of IV are not weak, so its variance estimation is not spoiled by IV bias.

Table 3

ESTIMATION RESULTS FOR HEADLINE INFLATION[1]

	1	2	3	4	5	6	7	8
Dep. variable	*Headline inflation:* π_t							
	Estimation sample					*Full sample*		
π_{t-1}	0.829 (0.000)	0.750 (0.000)	0.802 (0.000)	0.772 (0.000)	0.779 (0.000)	0.882 (0.000)	0.807 (0.000)	0.900 (0.000)
$\pi^f_{t,t+12}$	-	0.806 (0.032) [12]	0.890 (0.008) [12]	1.220 (0.003) [9]	1.144 (0.004) [9]	-	0.542 (0.000) [12]	0.356 (0.069) [9]
$\hat{y}_{t-1}$	0.210 (0.004) [1]	-	-	-	-	0.135 (0.043) [1]	-	-
$\hat{y}^f_{t,t+12}$	-	IV	−0.290 (0.397) [12]	-	-	-	IV	-
$\hat{y}^f_{t,t+24}$	-	-	-	IV	−0.012 (0.712) [1]	-	-	IV
Constant	0.543 (0.001)	−1.641 (0.075)	−2.200 (0.016)	−2.837 (0.008)	−2.702 (0.007)	0.400 (0.000)	−1.106 (0.004)	−0.699 (0.004)
J-statistic	0.000	0.879	0.520	1.307	1.218	4.496	4.065	3.688
J-stat. p-value	(0.979)	(0.644)	(0.470)	(0.520)	(0.269)	(0.033)	(0.130)	(0.158)
Sample	2000m5-2006m5	2002m2-2006m5	2002m2-2006m5	2002m9-2006m5	2002m9-2006m5	2000m5-2013m12	2002m2-2013m12	2002m9-2012m12
Number of observations	73	52	52	45	45	164	143	114

Notes: [1] p-value is shown in parenthesis; chosen lag is shown in square brackets, both below the coefficient estimates. Estimations with GMM. Weighting matrix estimation: covariance matrix inverse (with Newey-West HAC). Whitening lag specification: automatic with BIC, allowing up to three lags. IV stands for instrumental variable. Source: Author's elaboration.

Note that in both BL equations (1 and 4), the lagged inflation coefficients ranged from 0.83 to 0.88 (both significant). The output gap is significant with one lag (note that the first lag is allowed as it comes from a forecasted variable. In reality, delay in data release allows since two lags onwards). Equation 2 is the preferred with *Fwd (t + 12)*. In this case, the output gap is not significant with any lag between [1; 24]. Equation 3 shows the results when considering the 12-lag. As the data for t are sorted considering the h-period value, any lag between [1; 12] can be still considered as a forecasted value of π_t (in this case, lag 12 matches the targeted variable). Nevertheless, the output gap results as a valid IV. The FL coefficient accounts from 1.08 times bigger than the lagged coefficients in the first sample (Equation 2), declining to 0.67 times with the whole sample (Equation 7). The set of Equations 4, 5 and 8 mimics the results for *Fwd (t + 24)*. In this case, the decay in importance of the FL coefficient is more dramatic. For the first sample (Equation 4) accounts for 1.58 times to then decay to 0.40 with the full sample (Equation 8).

Table 4 shows the results for core inflation. Qualitatively these results are similar to headline but quantitatively their figures are more dramatic. The lagged inflation coefficient in the BL specification fluctuates between 0.77 and 0.91 (Table 4: Equations 1 and 6). The FL coefficient in the *Fwd (t + 12)* specification starts from 2.48 times the lagged coefficient, declining to 0.39 when considering full sample. Considering the *Fwd (t + 24)*, the FL coefficient accounts from 1.12 times with respect to the lagged, to just 0.19 with full sample.

All these results reveal instability in the parameters associated to FL inflation. To this end, in Figure 4, I display four graphs for each variable analyzing the evolution across the sample (recursive) of the key parameters: γ_b, γ_f, the t-statistic of γ_f, and the J-stat. p-value (keeping the same IV).[11]

[11] However, this analysis is simpler than that developed, for instance, in Swamy and Tavlas (2007) and Hondroyiannis, Swamy, and Tavlas (2009). In those studies, the authors make use of a

Table 4

ESTIMATION RESULTS FOR CORE INFLATION[1]

Dep. variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	Core inflation: $\tilde{\pi}_t$							
	Estimation sample					*Full sample*		
$\tilde{\pi}_{t-1}$	0.768 (0.000)	0.526 (0.031)	0.650 (0.033)	0.645 (0.000)	0.885 (0.000)	0.914 (0.000)	0.867 (0.000)	0.939 (0.000)
$\pi^f_{t,t+12}$	-	1.303 (0.106) [12]	1.034 (0.181) [12]	0.725 (0.034) [12]	0.361 (0.117) [1]		0.336 (0.000) [12]	0.175 (0.012) [12]
$\hat{y}_{t-1}$	0.212 (0.000) [1]	-	-	-	-	0.065 (0.030) [1]	-	-
$\hat{y}^f_{t,t+12}$	-	IV	−0.082 (0.494) [2]	-	-	-	IV	-
$\hat{y}^f_{t,t+24}$	-	-	-	IV	−0.050 (0.048) [1]	-	-	IV
Constant	0.634 (0.005)	−2.473 (0.146)	−2.302 (0.166)	−1.305 (0.073)	−1.090 (0.038)	0.217 (0.008)	−0.725 (0.000)	−0.351 (0.051)
J-statistic	2.086	0.167	0.007	3.556	2.577	1.490	3.845	2.800
J-stat. *p*-value	(0.148)	(0.919)	(0.933)	(0.168)	(0.108)	(0.222)	(0.146)	(0.246)
Sample	2000m5- 2006m5	2002m2- 2006m5	2002m2- 2006m5	2002m9- 2006m5	2002m9- 2006m5	2000m5- 2013m12	2002m2- 2013m12	2002m9- 2012m12
Number of observations	73	52	52	45	45	164	143	114

Notes: [1] *p*-value is shown in parenthesis; chosen lag is shown in square brackets, both below the coefficient estimates. Estimations with GMM. Weighting matrix estimation: covariance matrix inverse (with Newey-West HAC). Whitening lag specification: automatic with BIC, allowing up to three lags. IV stands for instrumental variable. Source: Author's elaboration.

Table 5

INSTRUMENTAL VARIABLES LIST

Equation	*Instruments*		*C-D F-statistic*[1]	*S-Y c.v.*[2]		*Relevant*
				10%	*25%*	*MSC*[3]
	Headline Inflation, Table 3					
1 6	Constant, π_{t-3} , π_{t-4} , $\hat{y}_{t-3}$	1 6	53.500	13.43	5.45	−2.600
2 3 7	Constant, π_{t-3} , $\pi^{f}_{t-24,t+24}$, $\hat{y}^{f}_{t-12,t+12}$, $\hat{y}^{f}_{t-25,t+12}$	2 7	77.040	16.87	6.28	−1.364
		3	0.226			0.221
4 5 8	Constant, π_{t-3} , $\pi^{f}_{t-24,t+24}$, $\hat{y}^{f}_{t-2,t+24}$, $\hat{y}^{f}_{t-20,t+24}$	4 8	7.208	16.87	6.28	−2.968
		5	7.273			−6.670
	Core Inflation, Table 4					
1 6	Constant, $\tilde{\pi}_{t-3}$, $\tilde{\pi}_{t-4}$, $\hat{y}_{t-2}$	1 6	91.704	13.43	5.45	−5.096
2 3 7	Constant, $\tilde{\pi}_{t-3}$, $\pi^{f}_{t-24,t+24}$, $\hat{y}^{f}_{t-12,t+12}$, $\hat{y}^{f}_{t-25,t+12}$	2 7	85.717	16.87	6.28	−4.612
		3	0.078			10.816
4 5 8	Constant, $\tilde{\pi}_{t-3}$, $\pi^{f}_{t-24,t+24}$, $\hat{y}^{f}_{t-2,t+24}$, $\hat{y}^{f}_{t-20,t+24}$	4 8	70.250	16.87	6.28	−4.933
		5	68.877			−9.043

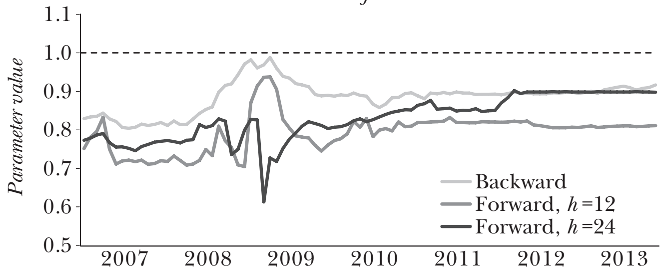
Notes: [1]C-D *F*-statistic stands for Cragg-Donald *F*-statistic. [2] S-Y c.v. stands for Stock and Yogo (2004) critical values. [3] MSC stands for moment selection criteria. See Hall et al. (2007). Source: Author's elaboration.

Figure 4

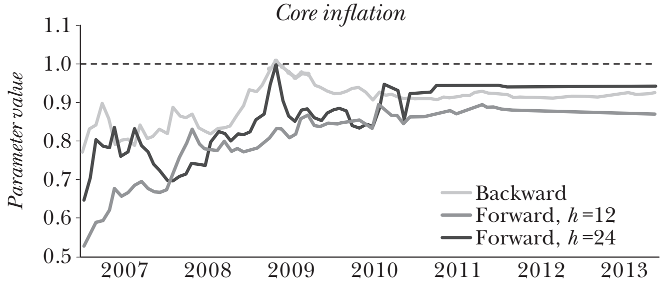
IN-SAMPLE RESULTS OF RECURSIVE PARAMETER ESTIMATION ACROSS FORECASTING SAMPLE[1]

A. Persistance parameter

Headline inflation

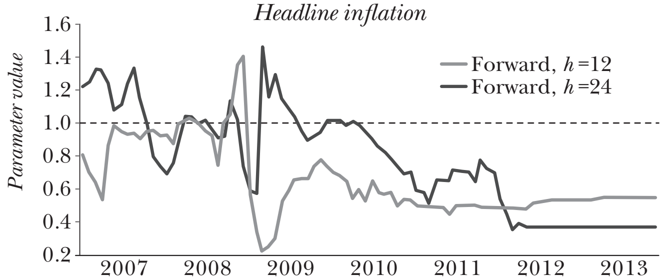


Core inflation

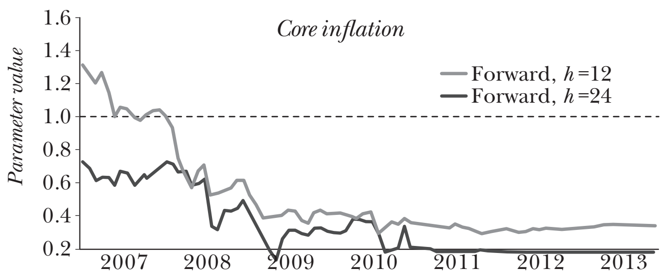


B. Forward-looking parameter

Headline inflation



Core inflation



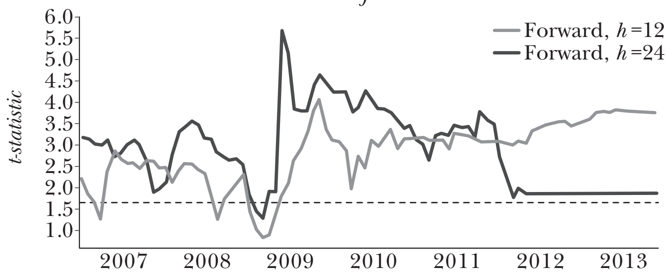
[1] A and B: Horizontal line = unit root bound.
Source: Author's elaboration.

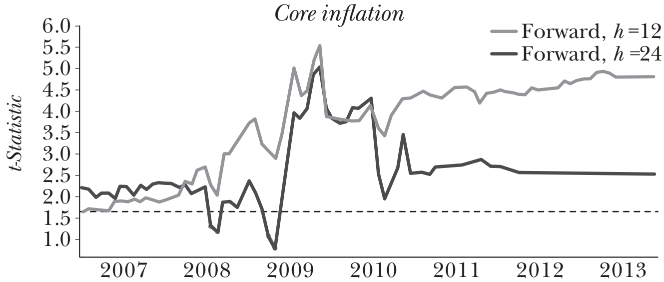
Figure 4 (cont.)

IN-SAMPLE RESULTS OF RECURSIVE PARAMETER ESTIMATION ACROSS FORECASTING SAMPLE[1]

C. *T*-statistic of the forward-looking parameter

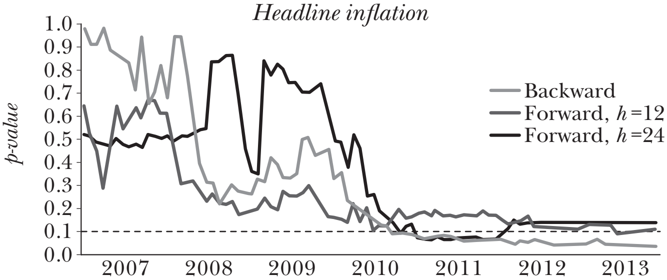
Headline inflation

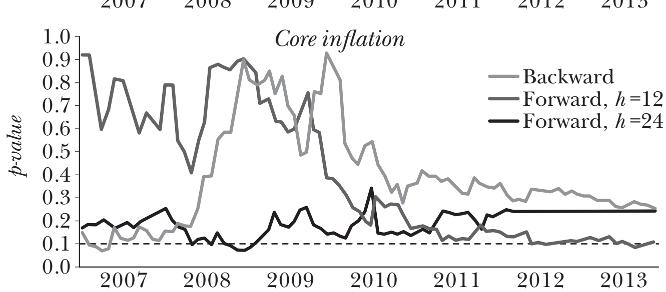




D. Hansen's *J*-statistic *p*-value

Headline inflation





[1] C: Horizontal line = Z_{α}^{-1}, where α is the probability-level(10%) of the inverse norma distribution. D: Horizontal line: *p*-value =10%.
Source: Author's elaboration.

These results show that for headline the persistence parameter moves slowly around 0.80 to 0.90 at the end of the sample. However, different results are obtained for the FL parameter. A major shift is adverted in the aftermath of the financial crisis. While in 2009 the parameter reaches values even greater than one, since 2012 that is around 0.50 with the two FL specifications. The parameter is almost always significant, and the IV are valid until 2013 for the FL specifications only.

For core inflation the situation looks similar. However, almost all estimates remain steady since late 2009. The lagged coefficients look similar for the three specifications around 0.90, while the FL coefficient below 0.40 (significant along the sample). The IV are consistent, especially with the *Fwd (t + 24)* specification.

From this analysis it is possible to conclude that there is a robust but low role for expectations when determining current inflation. This evidence is shared for headline as well as core inflation.

The results of robustness exercises when using headline inflation are the following.[12] In Table 6 there are shown the estimations using the real exchange rate within the preferred specification for each output gap version using two sample spans. Note that these results are obtained after fulfilling statistical significance with the full sample for a given lag –or some lags–, and then analyze the results with the reduced sample. By doing so, Equations 4 to 6 using full sample reveal a significant but unclear role for real exchange rate, ranging from −6.0% to 7.6%. When considering FL measures, the coefficient is significant negative around 6% to 3%. However, the chosen lag length –the only significant– does not remain significant within the estimation sample, see Equations 1 to

time-varying coefficient environment to reduce bias specification, finding a minor role for lagged inflation in four European countries.

[12] The robustness results using core inflation are not reported for the sake of space, but they are available upon request.

3. Even if they were significant, the coefficients are unstable in both sign and size. Hence, this version of the HNKPC is discarded for a further forecasting analysis.

Table 7 present the results when using oil price. It is noticed qualitatively same situation than before: significance with full sample –Equations 4 to 6–, and erratic results with the short sample –Equations 1 to 3–. The elasticity is close to zero possibly because the information provided by oil prices is already included in the FL component of inflation as De Gregorio, Landerretche, and Neilson (2007) argues. Again, these estimations are discarded for further out-of-sample analysis.

Finally, Table 8 shows the results when instead of output gap it is used the annual percentage variation of EAMI. In this case, the results seems promising for forecasting exercises since the variable is significant when it is included in both the first- and second-step regression and with the expected sign. Note that the output gap is completely substituted by the growth rate, even as an IV. This is a particular convenient result when the aim is to forecast since same specification could produce accurate forecasts with less information –an issue addressed later. According to Table 8, there is a major role for lagged inflation, whereas FL component has declined it importance as more observations are included. Using the estimation sample, the ratio between FL and lagged component is greater than unity, while with the full sample it accounts between 32% to 54% only.

3.2 Out-of-sample Results

The results are presented in terms of the *RMSFE ratio* between the preferred FL specification (*pivot*) and a competing model:

$$\text{RMSFE Ratio}_h = \frac{\text{RMSFE}_h^{Fwd\,(t+k)}}{\text{RMSFE}_h^{Competing}}. \tag{9}$$

Table 6

ESTIMATION RESULTS FOR HEADLINE INFLATION. REAL EXCHANGE RATE[1]

	1	*2*	*3*	*4*	*5*	*6*
Dep. variable:	*Headline inflation:* π_t					
	Estimation sample			*Full sample*		
π_{t-1}	0.837 (0.000)	0.758 (0.000)	0.772 (0.000)	0.887 (0.000)	0.764 (0.000)	0.852 (0.000)
$\pi^f_{t,t+12}$	-	0.799 (0.028) [12]	1.266 (0.017) [9]	-	0.778 (0.004) [12]	0.670 (0.002) [9]
$\hat{y}_{t-1}$	0.163 (0.017) [1]	-	-	0.265 (0.003) [1]	-	-
$\hat{y}^f_{t,t+12}$	-	IV	-	-	IV	-
$\hat{y}^f_{t,t+24}$	-	-	IV	-	-	IV
q_t	−0.007 (0.893) [16]	0.020 (0.304) [21]	0.002 (0.867) [21]	0.076 (0.042) [16]	−0.059 (0.068) [21]	−0.026 (0.060) [21]
Constant	0.550 (0.324)	−1.724 (0.042)	−2.973 (0.040)	0.314 (0.182)	−1.558 (0.619)	−1.496 (0.011)
J-statistic	0.000	0.060	1.475	0.000	2.237	1.022
J-stat. *p*-value	(1.000)	(0.806)	(0.220)	(1.000)	(0.134)	(0.311)
Sample	2001m5-2006m5	2002m2-2006m5	2002m9-2006m5	2001m5-2013m12	2002m2-2013m12	2002m9-2012m2
Number of observations	61	52	45	152	143	114

Notes: [1] *p*-value is shown in parenthesis; chosen lag is shown in square brackets, both below the coefficient estimates. Estimations with GMM. Weighting matrix estimation: covariance matrix inverse (with Newey-West HAC). Whitening lag specification: automatic with BIC, allowing up to three lags. IV stands for instrumental variable. Source: Author's elaboration.

Table 7

ESTIMATION RESULTS FOR HEADLINE INFLATION. OIL PRICE[1]

	1	*2*	*3*	*4*	*5*	*6*
Dep. variable:	*Headline inflation:* π_t					
	Estimation sample			*Full sample*		
π_{t-1}	0.819 (0.000)	0.866 (0.000)	0.775 (0.000)	0.919 (0.000)	0.926 (0.000)	0.744 (0.000)
$\pi^f_{t,t+12}$	-	0.499 (0.328) [12]	1.187 (0.004) [9]	-	0.326 (0.077) [12]	1.144 (0.008) [9]
$\hat{y}_{t-1}$	0.162 (0.004) [1]	-	-	0.197 (0.000) [1]	-	-
$\hat{y}^f_{t,t+12}$	-	IV	-	-	IV	-
$\hat{y}^f_{t,t+24}$	-	-	IV	-	-	IV
p_t	0.000 (0.966) [12]	−0.004 (0.300) [8]	0.000 (0.994) [12]	−0.009 (0.01) [12]	−0.008 (0.082) [8]	0.012 (0.096) [12]
Constant	0.547 (0.001)	−0.844 (0.465)	−2.745 (0.010)	0.477 (0.000)	−0.576 (0.191)	−2.901 (0.020)
J-statistic	11.067	1.054	1.346	0.000	1.910	0.000
J-stat. p-value	(0.000)	(0.304)	(0.245)	(1.000)	(0.082)	(0.988)
Sample	2001m1- 2006m5	2002m2- 2006m5	2002m9- 2006m5	2001m1- 2013m12	2002m2- 2013m12	2002m9- 2012m12
Number of observations	65	52	45	156	143	144

Notes: [1] p-value is shown in parenthesis; chosen lag is shown in square brackets, both below the coefficient estimates. Estimations with GMM. Weighting matrix estimation: covariance matrix inverse (with Newey-West HAC). Whitening lag specification: automatic with BIC, allowing up to three lags. IV stands for instrumental variable. Source: Author's elaboration.

Hence, figures below one are in favor of the *Fwd (t+k)* model, where $k = 12$ for headline and $k = 24$ for core. The results are presented in Table 9.

The results for headline show predictive gains in almost all cases. The exceptions are with respect to the RWK and the AR[*SB*] at $h = \{1; 3\}$. Note that when comparing to the other PC, the gains are qualitatively mixed: while higher gains are observed respect to *Fwd (t + 24)* at $h = \{1; 3\}$, it achieves 45.9% (= 1 − 0.541) when predicting at $h = \{6; 12\}$. The preferred specification is also better than both benchmarks when predicting at $h = \{6; 12\}$. According to the GW test, all differences are statistically significant except those with the BL specification.

The results for core reveals that the preferred specification *Fwd (t + 24)* outperforms the other FL specification, and both benchmarks when $h = 12$. The GW test reveals that only respect to *Fwd (t + 12)* at $h = \{1; 3\}$ the gains are statistically significant. However, note the BL specification is better at any horizon (but gains not significant). This result suggests that the lower variance of core respect to headline –i.e. its smoothness– inflates the relevance of the autoregressive term neglecting the inflationary FL variable (recalling that the forecast is made for headline).

In general, the out-of-sample exercise suggests that along with the ability of the HNKPC to explain inflation dynamics, it could be also considered as a valid benchmark model when forecasting at short-run. The predictive results for core inflation point out that its dynamics differs from those of headline, suggesting that core could be a process with higher memory (Granger and Joyeux, 1980). It is also suggested that the FL measures used are more related to the most volatile components of inflation. Conditional to the IV, the output gap measure plays a role within the BL specification delivering better results than its closer benchmark, AR[*SB*]. Further unexplored vignettes in this article may shed some light on core dynamics by analyzing some minor twists. For instance, nonlinearities in the (same) IV, and/or long-run forecasting horizons.

The results using the annual percentage variation of EAMI instead of output gap are presented in Table 10. As a robustness exercise, these results are compared to the baseline case. Hence, it is reported the ratio:

$$\text{RMSFE}_h \text{ Ratio Robustness}=\frac{\text{RMSFE}_h^{\textit{Annual variation}}}{\text{RMSFE}_h^{\textit{Output gap}}}, \quad (10)$$

where figures above unity implies a worst performance of the annual percentage change (*annual variation*) compared to the same specification when using output gap measure (*output gap*). In all the cases the baseline specification achieves a lower RMSFE except with the *Bwd* representing a predictive gain of 8%. Nevertheless, this gain is not statistically significant according to GW test.

Despite these results, the annual variation option still seems convenient and efficient given its simplicity. With headline inflation, the average *predictive loss* using the *Fwd 12* output gap across the horizons achieves 5%. This figure is even smaller at h = 1 and 3 around 2.8%. For the case of core inflation there is a similar situation. With *Fwd 12* output gap, the average predictive loss achieves 4.8%, and up to 2.4% at h = 1 and 3. Hence, the annual variation option seems as a valid second best alternative for inflation forecast.

4. CONCLUDING REMARKS

The aim of this article is to investigate to which extent FL measures of inflation help to explain inflation dynamics and their forecasts with a PC ensemble. This objective is tackled by analyzing the performance of the HNKPC, using a dataset of the Chilean economy, including inflation forecasts as a measure of inflation expectations.

To that end, I first estimate with GMM an unrestricted version of the HNKPC, to then compare its predictive power with a BL PC and traditional benchmarks predicting at h = {1; 3; 6; 12}-months-ahead.

Table 8

ESTIMATION RESULTS FOR HEADLINE INFLATION. ANNUAL PERCENTAGE CHANGE EAMI[1]

	1	*2*	*3*	*4*	*5*	*6*
Dep. variable:	*Headline inflation:* π_t					
	Estimation sample			*Full sample*		
π_{t-1}	0.944 (0.000)	0.710 (0.000)	0.807 (0.000)	0.968 (0.000)	0.886 (0.000)	0.876 (0.000)
$\pi^f_{t,t+12}$	-	1.056 (0.004) [12]	1.097 (0.031) [9]	-	0.290 (0.022) [12]	0.474 (0.041) [9]
y_{t-1}	0.063 (0.016) [1]	IV	IV	0.110 (0.000)	IV	IV
Constant	−1.123 (0.616)	−2.251 (0.011)	−2.610 (0.050)	−0.407 (0.006)	−0.499 (0.124)	−1.032 (0.106)
J-statistic	0.003	0.360	2.353	2.072	0.915	2.493
J-stat. *p*-value	(0.959)	(0.834)	(0.308)	(0.150)	(0.632)	(0.287)
Sample	2002m9- 2006m5	2002m2- 2006m5	2001m9- 2006m5	2002m2- 2013m12	2002m2- 2013m12	2001m9- 2013m9
Number of observations	73	52	57	164	143	145

Notes: [1] *p*-value is shown in parenthesis; chosen lag is shown in square brackets, both below the coefficient estimates. Estimations with GMM. Weighting matrix estimation: covariance matrix inverse (with Newey-West HAC). Whitening lag specification: automatic with BIC, allowing up to three lags. IV stands for instrumental variable. Source: Author’s elaboration.

Table 9

OUT-OF-SAMPLE RESULTS. RMSFE RATIO[1]

	Headline Inflation					Core Inflation					
	Bwd	*Fwd 12*	*Fwd 24*	*RWK*	*AR[SB]*	*Bwd*	*Fwd 12*	*Fwd 24*	*RWK*	*AR[SB]*	*No. of observ.*
$h=1$	0.966	1.000	0.791^{c}	7.757	9.360	2.507	0.707^{b}	1.000	10.300	10.865	91
$h=3$	0.716	1.000	0.636^{a}	1.242	1.511	2.162	0.721^{b}	1.000	2.454	2.576	89
$h=6$	0.507	1.000	0.605^{a}	0.373^{b}	0.416^{b}	1.901	0.815	1.000	0.980	1.099	86
$h=12$	0.541	1.000	0.787^{b}	0.177^{b}	0.193^{b}	2.359	0.909	1.000	0.534	0.595	80

Notes: [1]RMSFE ratio stands for RMSFE(*Pivot*)/RMSFE(*Competing*). GW test results: ^{a} $p>1\%$, ^{b} $p>5\%$, ^{c} $p>10\%$. Figures below one, in light gray; pivot in dark grey. AR[*SB*] stands for *stepwise backward* model selection; three lags chosen for headline and core inflation.
Source: Author's elaboration.

Table 10

OUT-OF-SAMPLE RESULTS. ANNUAL PERCENTAGE CHANGE EAMI (%EAMI)[1]

	Headline Inflation			Core Inflation			
	Bwd	*Fwd 12*	*Fwd 24*	*Bwd*	*Fwd 12*	*Fwd 24*	*No. of observ.*
$h=1$	1.913	1.027	1.057	3.451	1.012	1.130	91
$h=3$	1.698	1.030	1.127	2.895	1.024	1.148	89
$h=6$	1.363	1.118	1.318	2.158	1.068	1.120	86
$h=12$	0.920	1.021	1.697	1.197	1.089	1.016	80

Notes: [1]Each figure corresponds to RMSFE(%EAMI)/RMSFE (baseline output gap) for the same specification. Shaded cell: figure below unity.
Source: Author's elaboration.

The results show that the FL inflationary component is statistically significant when is included in the specification. In size, the preferred specification accounts from 1.58 to 0.40 times the lagged inflation coefficient; the latter figure considering whole sample. When considering short-term forecasting, I find predictive gains close to 45% (respect to the BL specification) and up to 80% (respect to the RWK) when forecasting at 12-months-ahead. However, these gains are not statistically significant. In sum, these results should be read carefully and the HNKPC just as a valid benchmark.

For robustness purposes, there are estimated same specifications with core inflation, plus an open economy analysis with real exchange rate or oil price. The in-sample results for core inflation support the existence of the HNKPC. Nevertheless, predictive results suggest that core could be a process with higher memory. The output gap plays a key role delivering better results than similar benchmark. None of the two openness measures used –real exchange rate nor oil price– deliver significant results in the reduced form.

Finally, the estimation using the annual variation of a monthly indicator of GDP instead of output gap deliver reasonable forecast accuracy but not as good as the preferred forecast – implied output gap measure.

Annex A. Output Gap Stability Analysis

One of the most desirable conditions for an unobservable variable is its stability. This can be understand as how robust is the measure while more observations are added to the sample. A more robust measure is that less invariant to new observations, and statistical inference can be carried out with a higher degree of reliability.

There are several measures towards stability assessment. Some common as well as useful measures are those contained in the X-12-ARIMA program in order to assess the seasonal adjustment quality, i.e. *sliding spans* and *revision history*.[13] In this appendix it is described and employed the revision history technique to determine the effect of forecast observations in the stability of the output gap measure, compared with the case where no observations are added. This last situation is often referred as the *end-of-sample* identification problem.

The revision history is defined as the difference between the earliest estimation of a given observation obtained when that observation is the last available and a later estimation based on all future data available at the time. Hence, this measure is specifically concerned with the effect of new information on the historical record of the output gap and the variance contribution to the estimation and the forecast afterwards.

The revision history is calculated as follows. Let $\hat{y}_{t|t} = y_{t|t} - y^{\tau}_{t|t}$ the output gap measure (in logs) calculated using $y^{\tau}_{t|t}$ as a measure of potential output. $y^{\tau}_{t|t}$ corresponds to the trend component of the decomposition $y_{t|t} = y^{\tau}_{t|t} + y^{c}_{t|t}$, obtained with the HP filter using available data until observation t. Now, suppose that the same $\hat{y}_{t|t}$ measure is obtained considering all future data available until observation T, $\hat{y}_{t|T}$. The revision history is defined as:

$$R_t = \hat{y}_{t|T} - \hat{y}_{t|t}. \tag{A1}$$

Note also that the decomposition $y_{t|t} = y^{\tau}_{t|t} + y^{c}_{t|t}$ can be made by using the actual plus h-forecast-augmented variable, $y^{f}_{t|t+h}$, to improve its stability. In this case, the output gap corresponds to $\hat{y}_{t|t,f} = y_{t|t} - y^{f,\tau}_{t|t+h}$, while the revision history to:

$$R_{t,f} = \hat{y}_{t|T} - \hat{y}_{t|t,f}. \tag{A2}$$

The comparison comprises R_t and $R_{t,f}$, as R_t is related to the purely BL case and $R_{t,f}$ to the *Bwd* output gap measure. In Figure A1, the first panel show the revision history across the sample for output gap based on the purely BL potential output (▼

[13] See Findley et al. (1990) and Findley et al. (1998) for details.

-point is the *most recent* estimation $\hat{y}_{t|T}$). The second panel exhibit the revision history for *Bwd*. In both figures there is also depicted the average of both measures. Note that the difference between purely BL and *Bwd* accounts for approximately 0.20 $(\simeq 0.78 - 0.59)$ basis points, while the variances are 0.83% and 0.59%, respectively. Hence, the procedure proposed by Kaiser and Maravall (1999) of adding forecast observations prior to any filtering procedure deliver a more stable measure of output gap. This last characteristic is desirable since this variable is prone to exhibit a larger measurement error which may turn to spoiling both interpretation and inference.

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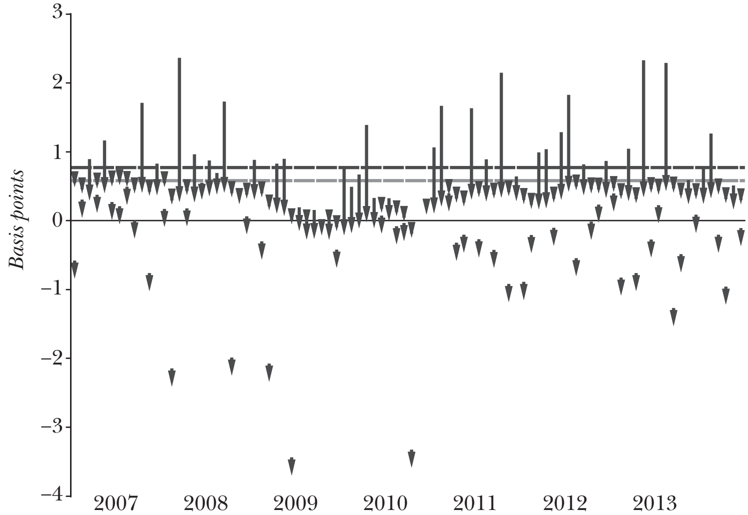
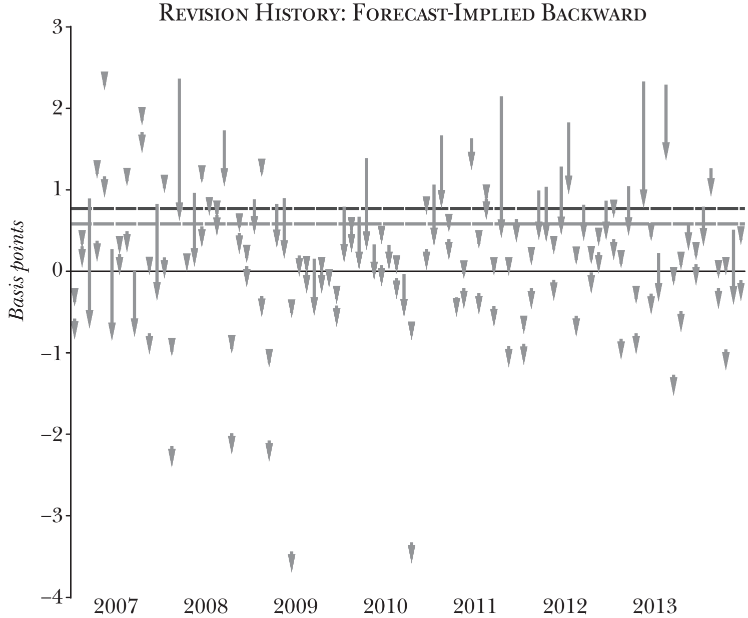
Figure A1

REVISION HISTORY COMPARISON

Revision History: Purely Backward



Revision History: Forecast-Implied Backward



▼ =Most recent.
Source: Author's elaboration.

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