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Hindsight vs. Real time measurement of the output gap: Implications for the Phillips curve in the Chilean Case*

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Abstract

We examine sources of output gap revisions in Chile and document how the informational content of these measures affects forecasts of inflation using estimated Phillips curves. Data and forecasts come from Monetary Policy Reports. Output gap revisions are found well behaved because cannot be predicted. We consider backward and forward-looking specifications and also real time, quasi-real time and final output gap estimates. Median and common-factor inflation present lower forecast errors. Results suggest that the passage of time is informative to measure output gap. Inflation forecasts more accurate are found using forward-looking specifications and CB of Chile Staff's gap estimates.

Resumen

Examinamos las fuentes de las revisiones de la brecha del producto en Chile y documentamos cómo el contenido informativo de estas medidas afecta los pronósticos de inflación utilizando curvas de Phillips estimadas. Los datos y pronósticos provienen de los Informes de Política Monetaria. Las revisiones de brecha se encuentran bien comportadas porque no se pueden predecir. Consideramos especificaciones donde la inflación se explica por inflación pasada y por expectativas; también se usan estimaciones de brecha de producto medidas en tiempo real, cuasi-real y final. La inflación mediana y extraida de factores comunes presentan errores de pronóstico más bajos. Los resultados sugieren que

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el paso del tiempo es informativo para medir la brecha. Los pronósticos más precisos se encuentran utilizando especificaciones con expectativas de inflación y estimaciones de brecha calculadas por el Banco Central de Chile.

I. Introduction

In the canonic model of monetary policy under inflation targeting the degree of slack in the economy plays a crucial role. The implementation of monetary policy relies heavily on the forecast of inflation and its relationship with the inflation target. This forecasting exercise depends, partially but crucially, on the measurement of this slack. This link between medium term inflationary pressures and broad demand and supply determinants, both in goods and in factor markets, is typically represented by the Phillips curve.

It is common to derive measures of slack in the economy from either the labor market or aggregate output. These macroeconomic variables are usually, and sometimes substantially, revised. However, a key difference between labor and output statistics is that the later are regularly revised following best practices.[2] Moreover, to gauge the slack in the economy a usual metric is the output gap, which is the difference between actual economic output and its potential, defined as the level of economic activity consistent with non-accelerating inflation.[3] Hence, the output gap is a special variable because it is mainly revised by two motives, given its construction. First, as mentioned, actual output is subject to frequent data revisions months and even years after initial releases. Second, measures of potential output are periodically re-estimated using different methodological approaches.

The first objective of this paper is to study revisions of the output gap over time and to decompose these revisions into their different sources, including changes in the detrending methods, which we call benchmark revisions, those due to the passage of time that change the estimation of potential

[2] For details see System of National Accounts (SNA), United Nations (2010). Statistical offices that prepare national accounts on a continuing basis over a number of years acknowledge that data sources change and improve. The need to revise data brings to the fore the conflict inherent in statistics between making the data as accurate as possible and making them as timely as possible. In Chile, data for the complete year is published in March of next year, i.e. year+1, along with complete data revisions of quarterly estimates. Output data is revised once more in March of year+2 and again in March year+3. Afterwards, data cannot be revised any more. An additional source of variability in quarter-on-quarter growth rates is due to estimation error of seasonal factors using standard X11-X13 methods.

[3] The Non-accelerating Inflation Rate of Unemployment (NAIRU) would be the equivalent to potential output in the labor market.

output, and revisions of the underlying output data. The second goal is to examine the relevance of these revisions to a key building block of the canonical model of monetary policy under inflation targeting, namely, the Phillips curve. We do this by assessing the quantitative implications of output gap revisions on the determinants of inflation through estimates of the Phillips curve. By understanding the nature of revisions to the output gap, as well as their implications for inflation forecasting and therefore the conduct of monetary policy, we are able to shed light on some relevant policy issues. For instance, to what extent do statistical changes in the actual measurement of output, rather than changing views about the level of potential GDP, drive the variation one sees in measures of the output gap? Are statistical revisions to the data truly new information, or rather are they revised back in later vintages and thus contribute mostly noise to the measurement of the output gap? Are simple detrending methods, such as the Hodrick-Prescott (HP) filter, better that the more judgmental and model-based estimates of output gap in providing real-time estimates of the level of the output gap that are closer to the final estimates? Is the impact of incoming data on output gap revisions too high?

Our paper makes two empirical contributions to the forecasting literature. First, in order to evaluate the source of output gap revisions, we present a way to classify revisions to output gap estimates from various sources.[4] Then, we apply with some modifications for the Chilean case a methodology already used in previous literature, testing several hypotheses following Aruoba (2008), but we focus on the output gap. Second, we study how forecast errors of inflation depend on different measures of the output gap using the Phillips curve, linked to the decompositions mentioned above, and following Orphanides and van Norden (2005).

Our main results are summarized as follows. First, with respect to the behavior of revisions, we find that revisions of Chilean output gap are generally positive and of a considerable variance, as found

[4] The set includes output gap estimates from simple filters as well as a rich database of CBCh staff's estimates, which provided a unique source of information, including methodological changes.

by Aruoba (2008) and Orphanides and van Norden (2002) for the output gap in the US. For staff estimates, after controlling by benchmark revisions, although the mean of revisions is positive and statistically significant —in contrast to using an HP filter— the variance of the same is heavily reduced compared to standard filters calculations. We also find that the main sources of staff's corrected revisions are due to methodological changes and data corrections, explaining around 78 and 20% of the mean of total revisions, respectively. When testing the predictability of revisions, we find that although past revisions are generally statistically significant, a random walk has overall lower mean average forecasting error than models including past revisions. These results for the output gap can be interpreted as evidence in favor of the *news* hypothesis of Mankiw and Shapiro (1984), in the sense that provisional estimates can be regarded as an efficient forecast of the final series and subsequent revisions reduce the forecast error by incorporating relevant new information.

Second, our results suggest that the estimation of the output gap using combinations of methods and judgement are more useful than simple HP filters because judgement methods present lower signal-to-noise ratio, in spite of some bias. We argue that the revisions of output gap do contribute to forecast inflation, which are composed by not only noise but add useful information (news). We find a role of output gap in forecasting various measures of core inflation with Phillips curves appropriately controlling by inflation expectations as well as real exchange rate movements, which to our knowledge has never been done before in this specific literature. In terms of inflation's forecasting performance, we find that: (i) the mere passage of time is informative to measure the output gap, i.e. inflation forecasts using final estimates provide smaller errors; (ii) forward-looking specifications yield slightly more accurate forecasts; and, (iii) staff's output gap calculation favorably compares with several alternatives. Results are robust. Median inflation and common factor inflation yield smaller forecast errors among core inflations considered.

Finally, we find some evidence of the flattening of the Phillips curve, although this is not linked to either the real time or final estimates of the output gap.

The structure of the paper is as follows. The following section describes the institutional background and the data. Section III defines output gap revisions, while Section IV reviews the methodology used to interpret and tests revisions. Section V presents the implications for forecasting inflation of using various measures of output gap. Section VI briefly analyze estimates of output gap parameters of Phillips curves. Finally, Section VII concludes.

II. Data

Given that we will study the relationship between inflation and the output gap, we need to specify clearly what measures of inflation will be used in the paper. The Central Bank of Chile (henceforth, CBCh) organizes its monetary policy implementation around an inflation target of headline consumer price index (CPI) inflation. In operational terms, monetary policy is conducted so that the most likely outcome is that expected two-year inflation is sufficiently close to the target. In this way, the conduct of monetary policy recognizes that exogenous and short-lived innovations can affect inflation in the short run, and that monetary policy actions take time to affect the economy.[5] Therefore, we devote more attention to core inflation measures in our analysis, as in Pichette *et al.* (2019). Intuitively, core inflation is easier to monitor and predict following the evolution of wages, measures of capacity utilization, the output gap, etc. In particular, we study four core inflation measures: CPI inflation excluding food and energy, the median CPI inflation, common factor inflation and trimmed-mean inflation.

Inflation excluding food and energy is publicly available, whereas the other three measures are calculated out of official data by the staff of the CBCh. First, the median inflation is constructed following subcategories of CPI inflation published by the National Bureau of Statistics of Chile, seasonally adjusted. After ordering monthly inflation from less to high inflation subcategories, we cumulate up to 50% of share of the CPI. The category that accumulates 50% is taken to construct

[5] See Central Bank of Chile (2007).

monthly inflation and then cumulated to obtain quarterly inflation. Studies for the US economy found that the median inflation seems to provide a better signal of trend inflation than headline and other core inflation measures. Besides, median inflation is better to forecasting PCE inflation in the near and longer term than the core PCE.[6] Second, the methodology of calculation of trimmed-mean inflation for the case of Chile is documented by Córdova *et al.* (2008). Third, the common factor inflation is calculated using standard principal components techniques (for parsimony we use the fitted four principal components model calculated on CPI's subcategories).[7]

In the theoretical literature on Phillips curves, inflation is traditionally explained by marginal costs, expected and past inflation.[8] For this empirical application, we consider: (i) one-year ahead observed inflation expectations collected through surveys of market participants[9]; and (ii) one-quarter and four-quarter ahead inflation forecasts included in each Monetary Policy Report issued by the CBCh (henceforth, MPR), which are published in excel files since March 2018.

Regarding the output gap, we use the data considered in the forecasting rounds included in each MPR from May 2000 to June 2018. This dataset includes quarterly real-time GDP, potential GDP and output gap series. More precisely, the output gap measure considered for monetary policy focuses on

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[6] See Bryan and Cecchetti (1994), Bryan (2007), and Ball and Mazumder (2019).

[7] Inflation measures are usually not revised, though there are some exceptions, see Croushore (2019). The Bureau of Statistics of Chile updates consumption baskets every five years to better reflect variations in consumption's patterns following international practices. Rubio and Sansone (2015) provide longer time series of core and headline inflation. We take from that study prices' subcategories, which do not change, to compute the common factor inflation. As explained in the Data Appendix, this calculation uses all information available at the moment of writing this article. It should be noticed, therefore, that the exact inference of principal components is conditional on this particular sample and it is subject to statistical estimation error. This estimation error will tend to decrease, as the sample enlarges. The common factor inflation excludes rare behavior of particular items due to unspecific reasons and is comparable with median inflation. Results that will be presented in section V.3 tend to confirm that forecasts properties of the common factor inflation are quite comparable with those obtained using median inflation.

[8] For a survey of the New Keynesian Phillips curve, see Clarida, Gali, and Gertler (1999). They point out that this model is widely used in theoretical analysis of monetary policy. To our knowledge, this is the first paper that considers inflation expectations in inflation determination when considering the role of output gap revisions.

[9] https://www.bcentral.cl/en/web/guest/expectativas-economicas .

those components of economic activity that to a large extent determine inflation. That measure of GDP excludes mining, fisheries, electricity, gas and water.

Thus, the database used has two-dimensional array shape for each variable: inflation and inflation forecasts, actual GDP, potential GDP and output gap. Given the methodology we will develop later, the forecasts of the output gap do not enter into the Phillips curve specifications. In this data set, for each variable the typical array is a rectangle, with a sort of upper triangular shape, with 64 columns (each denoting a MPR quarter) and rows that refer to quarters. [10] For the oldest MPR of May 2000, the last data observed is 1999Q4 and two-year forecasts are available, i.e., from 2000Q1 to 2001Q4. In contrast, the 64th column contains information taken from the MPR of June 2018.

Finally, quarterly output data is seasonally adjusted. The seasonal adjustment factors are taken from each MPR. Seasonally adjusted output data is published since 2013.[11] Seasonal adjustment factors are prone to revisions in the short run and we consider them as statistical noise in this study.

III. How to interpret the output gap revisions? Some definitions

The process of forecasting inflation to inform monetary policy making at the CBCh can be abstracted into the following procedure. During each quarter, using the latest information available, a *real time* estimate of the output gap for the most recent quarter available is constructed, which is then used as an input into the inflation forecasting process as well as an input to assess the stance of monetary policy. As time goes by, in the following quarter a new estimate of the output gap is constructed, which will not only add one more observation to the series, but also will likely provide revisions to output gap estimated measures for previous quarters.

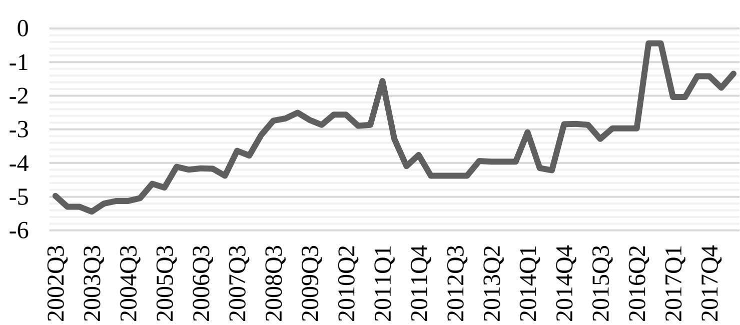
[10] Since May 2000 to September 2009 the CBCh issued MPRs in January, May and September, i.e. three times per year. It should be noticed that each MPR issued in September added two data points, whereas other MPRs just one data point. Since December 2009 the MPRs have been issued each quarter.
[11] See Cobb and Jara (2013) for the documentation of the official methodology.

The most recent observation is very informative for policy analysis because it provides the timeliest measure of the cyclical stance of the economy. We define the *real time output gap*, as the collection of the first estimate of the most recent output gap measure for each quarterly MPR. This *real time* staff estimate represents the first announcement of every output gap data for each point in time. Note that the output gap of past dates is likely to be revised. This information could be of second order of importance due to the real time nature of the policymaking process, or it could be relevant if it motivates changes in the detrending methodologies.

As an illustration, Figure 1 reports the output gap estimated for the first quarter of 2002 from the first available vintage of data, namely MPR of September 2002, to the last in our sample, the MPR of June 2018. It is evident that for this particular quarter there have been frequent revisions, so that for instance the most recent inference more than halved its magnitude in the last two years. This is not a particular result for this quarter, but rather to all quarters in the sample. Below we will distinguish between methodological changes and revisions in data that are generating these revisions. Further bellow, what we mean with methodological changes will be more explicit.

Figure 1. Output gap of 2002Q1

(Percentage)



Source: CBCh's Monetary Policy Reports.

Some notation borrowed from related literature will facilitate our analysis. Let $y_{t,t+1}$ denote the initial estimate (or *vintage*) of the output gap, realized at time t but for which data was known at time $t+1$.

The related literature usually defines the *final value* as the latest available vintage of data, in our sample this would be June 2018.[12] However, as argued by Aruoba (2008), the most timely observation of the variable may not necessarily be the best choice due to benchmark revisions. As shown in Figure 1, recent revisions consider more data as well as improved estimation methods. Therefore, to obtain comparable revisions of output gap over time we should control for changes in methodology.

In order to avoid including too many benchmark revisions, for the purpose of this paper we define the final revisions as the change on the series since the initial announcement and its two years ahead value: $r_{t,f} \equiv y_{t,f} - y_{t,t+1}$, where $y_{t,f} \equiv y_{t,t+8}$.[13] Alternatively, we considered three years and results remain very similar because data revisions between two and three years tend to be relatively small. The main results and conclusions are preserved using the last available data available at MPR of June 2018, see Annex C.

The magnitude of benchmark revisions can also be noted in panel A of Figure 2, which compares the latest data available of the output gap, and the real time estimate at each point in time: $y_{t,t+1}$, for *t*: 2001Q1, 2001Q2,…, 2018Q2. The difference between these two series is, for some subsamples, quite persistent —for example in the period 2001-2008 and 2012-2014— but in other subsamples, these differences vanish. As a first pass, to isolate the changes in data from the changes in methodology, we re-defined the final value as the latest available value *before* selected dates when the CBCh applied clear methodological changes to the measure of trend output, i.e. benchmark revision. From the examination of historical data used for monetary policy forecasting at the CBCh, we identify four major changes in the detrending methods used to calculate the output gap from 2000 to 2018.[14] Let us define the dates of these benchmark revisions as *t=BR*.

[12] See Orphanides and van Norden (2002), Chumacero and Gallego (2002).

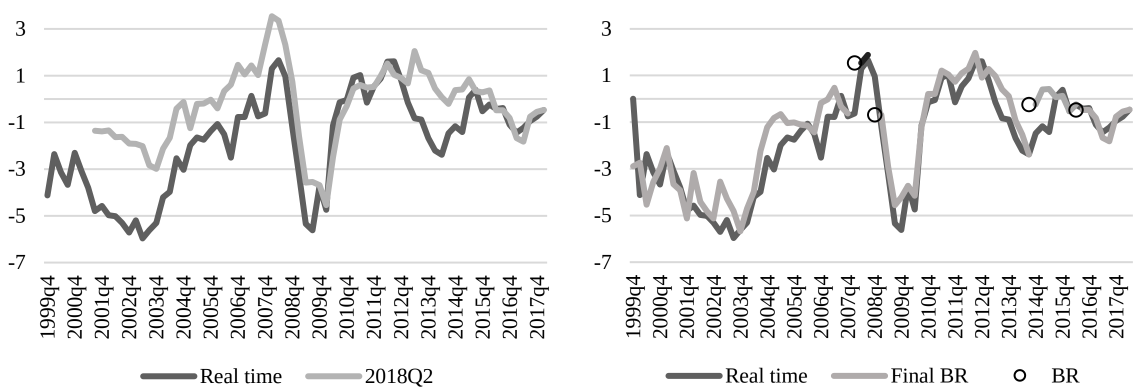
[13] The *i*-th revision of the series referred to quarter *t*, after its initial announcement, $t+1$, would be defined as: $r_{t,t+1+i} \equiv y_{t,t+1+i} - y_{t,t+1}$.

[14] Detailed methodological changes are reported in the Annex A. In September 2015 official methodology applied at the CB of Chile distinguished two concepts of output: trend and potential; see Albagli and Naudon, (2015). The former is calculated using the production function approach similarly as other international

We define $y_{t,f}^{BR}$, as the latest available data *before* a benchmark revisions and then construct the final revisions net of methodological changes, $r_{t,f}^{BR} = y_{t,f}^{BR} - y_{t,t+1}$, which compares real time and final estimates that were calculated within benchmark revisions. This is a rough way to compare series that were computed using the same detrending methodologies, without eliminating the revisions within the two years horizon. It is only a rough estimate because it assumes that the methodological changes are additive. Results in Panel B of Figure 2 show that revisions are still usual and sometimes of a significant size, but the contamination produced by the methodological revisions is reduced.

Figure 2. Real time and final output gap time series

A. Real time and latest available at 2018Q2 B. Latest available *before* benchmark revisions (BR)



Source: authors' own calculations from CBCh's MPRs. Final is taken from MPR of June 2018.

As proposed by Orphanides and van Norden (2002), we construct an *alternative real-time* estimate of the output gap that keep the detrending methodology constant, but incorporate revisions to the level of output from statistical sources, ($y_{t,t+1}^{T}$). This measure provides evidence on how the arrival of new real-time data affects output gaps in general, keeping the detrending method constant. For this purpose, we use standard statistical filters as the detrending method.

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institutions do, e.g., the Congress Budget Office, the European Comission, etc. The classical growth literature identifies the level of long term growth with the growth rate of productivity, capital accumulation and demographic trends, without considering the inflationary effects because in the long term it is assumed that the so-called "classical dichotomy" holds. Potential output, in contrast, is informed with statistical filters that link the inference of the output gap with a level of non-accelerating inflation around the target (using a Phillips curve and additional assumptions).

In addition, we calculate the *quasi-real* output gap estimate ($y_{t,t+1}^{T,Q}$) following Orphanides and van-Norden (2002). Quasi-real output gaps are generated conducting rolling estimations with the same detrending methodology, but based on the latest vintage of data. That is, the output gap at period *t* is calculated using observations 1, 2,…, *t* of the latest vintage to estimate the long-run trend and the deviations around it. This estimate therefore keeps the detrending methodology constant, and has only one vintage of data. Changes in output gap estimates at a specific point in time will therefore be linked to the simple passage of time. Table 1 summarizes the types of revisions.

Table 1. Specifications of Revisions of the Output Gap

Methodology to calculate real time series of output gap	Final revision
Bank's staff estimates	$r_{t,f} \equiv y_{t,f} - y_{t,t+1}$
Bank's staff estimates, using benchmark revisions as the final vintage	$r_{t,f}^{BR} \equiv y_{t,f}^{BR} - y_{t,t+1}$
Estimates by detrending a rolling sample of real time series	$r_{t,f}^{T} \equiv y_{t,f}^{T} - y_{t,t+1}^{T}$
Estimates by detrending a rolling truncated sample of the final vintage	$r_{t,f}^{T,Q} \equiv y_{t,f}^{T,Q} - y_{t,t+1}^{T,Q}$

Note: This table introduces notations.

Table 2 displays the sources of revisions of output gap using the notation presented in Table 1, decomposing total revision into three sources:

i. Methodological changes —in the calculation of output gap or potential output— can be measured by comparing the revisions of real time output gap without controlling by any methodological change ($r_{t,f}$), with those revisions that were calculated using the same output data but one consistent detrending method through the whole sample ($r_{t,f}^{T}$). Since both series were calculated using the same output data and are equally affected by the passage of time, the differences between both revisions are explained by the methodologies used.

ii. The mere passage of time changes the inference about potential output, changing therefore the output gap series. This source can be captured by the revision of quasi-real time series ($r_{t,f}^{T,Q}$), which is estimated using the same methodology over recursive rolling samples of the final series, i.e. it uses the same methodology and output final series for calculating output gap every point in time, but the size of the sample changes by adding one observation each time.[15]

iii. Finally, revisions associated to data corrections can be identified as the difference between the revisions of real time series ($r_{t,f}^{T}$) and quasi-real estimations ($r_{t,f}^{T,Q}$). Both revisions use the same methodology and are subject to the pass of time, however, since the quasi-real output gap is calculated using only subsamples of the final series and the real time series uses the data available in each point of time, the difference between the two series will be solely explained by data revisions.

Table 2. Sources of Revisions of the Output Gap

Sources	Calculation
(i) Methodological changes to calculate output gap (benchmark revisions).[16]	$r_{t,f} - r_{t,f}^{T}$
(ii) Changes in trend (or potential output) because of new observations.[17]	$r_{t,f}^{T,Q}$
(iii) Data revisions (national accounts).	$r_{t,f}^{T} - r_{t,f}^{T,Q}$
$Total\ revision \equiv$ (i) + (ii) + (iii)	$r_{t,f} \equiv (r_{t,f} - r_{t,f}^{T}) + r_{t,f}^{T,Q} + (r_{t,f}^{T} - r_{t,f}^{T,Q})$

Note: This table adds notation to distinguish sources of revision of output gap.

Whereas following empirical strategies of Aruoba (2008) and Orphanides and van Norden (2002) are useful to inquire on the properties of Chilean GDP revisions, the direct application to output gap revisions is not trivial. As we have shown with different measures of output gap, potential output methods are known to estimate it with some degree of uncertainty.[18] Section IV will report evidence from econometric exercises aimed at interpreting revisions for different output gap measures.

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[15] See Network of EU IFIs (2018, p. 66 and 67) for a conceptual distinction and discussion of one-side vs two-side filtering in the context of the Kalman filter. Notice, that in the conceptual framework we developed, quasi-real time revisions capture those differences.

[16] The difference between the initial announcement of a variable and its final value could be interpreted as a massive revision of past data or merely because of a change of scale (sometimes statistical assumptions are needed to construct longer time series, e.g. backward interpolations). The methodology (T) used to calculate $r_{t,f}^{T}$ is the benchmark detrending method to estimate the methodological differences with staff'estimates ($r_{t,f}$).

[17] More information changes inference of potential output and therefore, the potential output gap.

[18] Network of EU IFIs (2018) provides a broad literature review on output gap estimates from the perspective of a fiscal authority. In this paper we focus on the implications for forecasting inflation, see Section V.

IV. Interpreting and testing revisions

IV.I. Are revisions well behaved?

Aruoba (2008) focuses on vintages of data released by official US Statistical Offices and investigates whether revisions are well behaved. He assumes that if the revisions to macroeconomic variables are due to the arrival of new information that was not available at the time of the initial announcement, then well-behaved revisions should be rational forecast errors. The first condition for the revision is to have zero mean. This would imply that the initial announcement is an unbiased estimate of the final value. Second, the variance of the revision is expected to be relatively small compared to the variance of the final value. Third, the revision should be unpredictable given the information set at the time of the initial announcement. If, on the contrary, the revisions were predictable, it would imply that the initial announcement is not an optimal forecast of the final value and a better forecast can be estimated. For the final revision, the three *properties* can be summarized as follows:

$$(P1): E\left(r_{t,f}\right) = 0$$

$$(P2): var\left(r_{t,f}\right)\ is\ small$$

$$(P3): E\left(r_{t,f} \middle| I_{t+1}\right) = 0$$

where I_{t+1} is the information set at the time of the initial announcement. We test whether output gaps satisfy the three statistical properties to consider them well behaved.[19]

Table 3 reports summary statistics for the output gap revisions of the Bank's staff estimates, the staff estimates corrected by benchmark revisions, our own calculations of real output gap using HP filter and our own calculation of quasi-real output gap using HP filter.[20] The mean of the output gap is

[19] Exercises for revisions of GDP and of potential GDP are reported in Annex B.

[20] Detailed results for different revisions' horizons and filtering methods are reported in Table C1, Annex C. Benchmarking with standard filters seeks to maintain an estimation methodology invariant. For example, despite we are aware of several HP filter problems described by Hamilton (2018), we still think it is a useful benchmark to count with. Besides, we use the standard $\lambda = 1600$, even though we are aware of the studies by

significantly positive for staff estimates of output gap (almost 1.2), even after controlling by benchmark revisions (which reduces the mean to 0.4). In other words, on average, the final estimate of the output gap for a given quarter is 1.2 percentage points different from the first vintage; however, this difference is reduced to one third after the output gap is corrected by significant methodological changes, i.e. level's adjustment of potential output. Still, after benchmark revisions magnitudes are statistically different from zero, suggesting evidence against the zero mean hypothesis (P1).

It is noteworthy that, if instead of using the staff estimates (with our without benchmark revisions), we calculate output gaps with a statistical filter such as the HP, the mean revision is almost cut down to half (0.26).[21] Moreover, quasi-real estimates of the output gap with the HP filter indicates almost zero average revisions (0.03). This suggests that most of the positive bias of output gap revisions comes from data revisions and benchmark revisions, instead of changes in trend (or potential output) due to new incoming data from the passage of time.

The average magnitude of the revisions is one important statistic to gauge the relevance of different methodologies. However, a second one is the volatility of such revisions. The second row of Table 3 shows that the standard deviation of output gap revisions is reduced after controlling by benchmark revisions (from 1.4 to 1.0), and that it is lower than the standard deviation of the output gap using the HP filter, for both real and quasi-real estimates. This implies that although the mean of output gap revisions is significantly reduced when using a standard filter, the volatility of revisions increases.

The last row of Table 3 reports the noise-to-signal ratio, a measure to assess the size of revisions relative to the original variable, defined as the ratio between the standard deviation of revisions and the standard deviation of the final value of the output gap. As shown in Table 3, the noise-to-signal ratio for final revisions after controlling by benchmark revisions is 0.62, however this number grows

Restrepo and Soto (2004) and Mies and Valdés (2003) that use an estimated λ=3024 for Chile. We argue that our point is robust either using the HP filter with other λ or altenative filters.

[21] Using Band Pass (BP) filter, the mean of revisions results to be positive and statistically significant, with a slightly lower absolute mean and standard deviation than using HP filter.

up to 0.8 when using an HP filter. As found by Aruoba for real output in the US with a noise-to-signal ratio around 0.4, final revisions of Chilean output gap are sizable enough to be considered evidence against (P2).

Table 3. Output Gap Final Revisions Summary Statistics

Statistic	$r_{t,f}$	$r_{t,f}^{BR}$	$r_{t,f}^{HP}$	$r_{t,f}^{HP,Q}$
Mean*	**1.169**	**0.407**	0.263	0.028
Standard Deviation	1.415	1.024	1.698	1.874
Noise-to-signal ratio	0.863	0.625	0.801	0.884
Sources of Revision (Mean)				
(i) Methodology ($r_{t,f} - r_{t,f}^{HP}$)	77.5%	35.4%		
(ii) Trend ($r_{t,f}^{HP,Q}$)	2.4%	6.9%		
(iii) Data ($r_{t,f}^{HP} - r_{t,f}^{HP,Q}$)	20.1%	57.7%		

Source: Authors' elaboration.
Notes: (*) Bold values indicate that the null hypothesis of zero mean is rejected at the 0.05 level of statistical significance. More specifically, we regress revisions on a constant. The maintained null hypothesis is that the constant is zero. Sources of revisions reported are identified using an HP filter as benchmark methodology. Super-indices' abbreviations are as follows: BR denotes benchmark revisions, HP denotes Hodrick-Prescott filter, Q denotes quasi-real estimation.

Table 4. Results of the News vs Noise Hypothesis for Final Revisions of Output Gap

	Noise hypothesis		News hypothesis	
	$y_{t,t+1} = \alpha_1 + \beta_1 y_{t,f} + v_t^1$ H0: $\alpha_1 = 0,\ \beta_1 = 1$		$y_{t,f} = \alpha_2 + \beta_2 y_{t,t+1} + v_t^2$ H0: $\alpha_2 = 0,\ \beta_2 = 1$	
	α_1	β_1	α_2	β_2
$y_{t,f}$	**-1.430**	**0.671**	**1.449**	**1.143**
$y_{t,f}^{BR}$	**-1.385**	**1.103**	**0.718**	**0.602**
$y_{t,f}^{HP}$	-0.275	**0.554**	0.116	**0.492**
$y_{t,f}^{BP}$	**-0.828**	**0.559**	**0.926**	**0.994**
$y_{t,f}^{Q,HP}$	-0.036	**0.570**	0.004	**0.459**
$y_{t,f}^{Q,BP}$	**-0.644**	**0.601**	**0.717**	**0.947**

Source: Authors' elaboration. Note: Bold values indicate statistical significance at the level of 0.05.

Given the inconclusive results of the joint hypothesis test, we follow Aruoba (2008) and test the predictability of the revisions in an extended model. As previously argued, if revisions are merely explained by a measurement error /noise on preliminary estimates, we could find a forecasting model for revisions that can perform better than the one implied by (P3), with conditional mean zero.

The following models are estimated:

M1: $r_{t,t+1+i} = \alpha + \gamma y_{t,t+1} + \sum_{j=1}^{s} \beta_j r_{t-j,t+1} + \sum_{j=1}^{4} \lambda_j Q_t^j + \delta t + \varepsilon_t^1$

M2: $r_{t,t+1+i} = \alpha + \gamma y_{t,t+1} + \sum_{j=1}^{4} \lambda_j Q_t^j + \delta t + \varepsilon_t^2$

M3: $r_{t,t+1+i} = \alpha + \varepsilon_t^3$

M4: $r_{t,t+1+i} = \varepsilon_t^4$

where for M1 the dependent variable is the i^{th} revision after the initial announcement and the explanatory variables are a constant α, the initial announcement, revisions to past quarters announced at date $t+1$, quarterly dummy variables and a linear trend. If past revisions included have some predictive power in explaining future revisions, then this predictability could be considered evidence against the news hypothesis (P3). The selection of past revisions to be included in M1 is conducted as follows. M1 is estimated including each past revision in the last two years separately, and adding one at the time. Between all possible specifications of M1, we choose the model with the lower root mean squared errors (RMSE). Seasonal dummies are added because there could be some seasonality associated to specific revision schedules of the CBCh. M2 includes first vintage and other deterministic variables, while M3 includes only deterministic variables, such as seasonal dummies and trend. ε_t^1, ε_t^2, ε_t^3, ε_t^4 are error iid terms.

Following Aruoba (2008), we first test for the joint significance of all past revisions in M1 and then compare the RMSE of every model against the *news* null hypothesis, i.e. that a random walk (M4) is the real model.

Table 5 reports results of Aruoba's (2008) exercise for final revision.[22] From Table 5A, the first result that stands out is that past revisions are generally statistically significant. Only for the Bank's estimates of output gap ($r_{t,f}$) past revisions are not significant, this model presents the lower R2 statistic (0.015) compared to other revisions specifications (around 0.5 to 0.6). However, the random

[22] Detailed results for different revisions' horizons and filtering methods are reported in Table C2, Annex C.

walk model reports a lower RMSE than any of the models including past revisions for all output gap specifications (see Table 5B).

Table 5. Results of the Estimation Exercises for Output Gap

A. M1 results

Output Gap	Past revisions included	Wald $\beta_j = 0$	Adj. R^2
$r_{t,f}$	Rev2q	0.385	0.015
$r_{t,f}^{BR}$	Rev1¾y	**0.000**	0.511
$r_{t,f}^{HP}$	Rev2y	**0.000**	0.513
$r_{t,f}^{Q,HP}$	Rev2y	**0.000**	0.587

B. Comparing RMSE

Output Gap	M1/M4	M2/M4	M3/M4
$r_{t,f}$	1.283	1.319	1.335
$r_{t,f}^{BR}$	1.246	1.260	1.781
$r_{t,f}^{HP}$	1.519	1.716	2.092
$r_{t,f}^{Q,HP}$	2.492	2.828	3.656

Source: Authors' elaboration.

Notes: Bold values indicate that the null hypothesis stating that past revisions exert no influence on the dependent variable of regression (M1) is rejected at the 0.05 level of statistical significance. M1 includes constant, initial announcement, past revisions, trend and seasonal dummies. M2 includes constant, initial announcement, trend and seasonal dummies. M3 includes a constant. M4 is random walk model. Abbreviations: BR denotes benchmark revisions and HP denotes Hodrick-Prescott filter.

To summarize, we find that revisions of the output gap —regardless the detrending method— are positive and have a considerable variance, which is evidence against the well-behaved revisions' properties of zero mean and small size (P1 and P2). Staff's revisions corrected by benchmark revisions present a statistically significant positive mean, in contrast to using an HP filter; however, the variance of corrected staff estimate revisions is smaller than standard filters, which is good. We also find that the main sources of staff's corrected revisions are methodological changes and data revisions, explaining around 77.5% and 20.1% of the mean of total revisions respectively. These results motivated the estimation of further models to evaluate the predictability of revisions (P3): if revisions are predictable, then they could be interpreted as corrections of the initial announcement and not because of new information is added to an efficient forecast of output gap. We find that for final revisions, although past revisions are generally statistically significant, a random walk has overall lower RMSE than models including past revisions. These results for output gap can be interpreted as evidence in favor of the *news* hypothesis (P3), this is that provisional estimate can be regarded as an efficient forecast of the final series and subsequent revisions reduce the forecast error by incorporating new information.

V. Implications for forecasting inflation

V.1. Phillips curve

This section empirically studies the capacity of output gaps to forecast inflation using Phillips curves. Building upon previous sections' evidence on sources of output gap revisions, this paper revisits the topic focusing on a broader set core inflation measures. Briefly, our findings suggest that core inflation measures that rule out extreme price variations or changes in relative prices, such as the median inflation, are generally better predicted by output gaps.

Studies in the literature typically evaluate the performance of Phillips curve models in forecasting inflation using real time, quasi-real time and final output gaps obtained with various methods. Orphanides and van Norden (2005) conclude that models of Phillips curve are no better than univariate models when forecasting inflation in the US. In particular, they find that forecasts accuracy do not improve if the models are estimated with real time estimates of the output gap instead of the final version of the output gap. More recently, Edge and Rudd (2016) using FED staff's forecasts of the output gap and inflation forecasts consistent with output gaps find no significant improvement in the predictability of inflation using real time output gaps. Cayen and van Norden (2002) study the Canadian case applying similar methodology and find that Phillips curve do not improve upon standard autoregressive models. More recently, Champagne *et al.* (2018) report similar results, but importantly they do find significant evidence in favor of higher forecasting performance obtained from Phillips curves implemented with staff output gap estimates. They point out that evidence in favor of the Phillips curve is more clear in a more recent subsample (among other things, they point out that this is so because the output gap is more stable due to improvements in the methodology applied by staff).

In Chile, evidence provided by Pincheira and Rubio (2015) is relevant because they conduct a real time exercise and find little evidence of inflation predictability when using real time information. Results more in favor of inflation predictability using Phillips curves is found by Fornero and Naudon

(2016). The gain is found by specifying Phillips curves to predict tradable goods separated from non-tradable goods core inflation (inflation excluding food and energy). In addition to a simple quasi-real time output gap, HP filtered, specifications include the real exchange rate depreciation. The main finding is that predictive ability of aggregate inflation is improved when combining forecasts of particular (tradable and non-tradable) Phillips curves. We will come back to estimation issues that apply to small and internationally open emerging economies later on.

Admittedly, part of our attention is devoted to check whether our findings using Chilean data are comparable with results reported in the literature that focus on Canada and US. However, additional novel evidence is provided. First, we use inflation expectations from surveys as well as historical staff's inflation forecasts and changes in real exchange rates. Second, we find that output gap measures studied in the previous section play a role in forecasting measures of core inflation.

The methodology commonly used in the literature hinges upon the so-called direct forecasting method or in-sample Granger-causality tests (Bryan and Cecchetti, 1994). The idea is to estimate parameters directly within the projection of *h*-periods ahead inflation. The following models are considered:

$$\pi_{t+h} = c + \sum_{p=1}^{4} \alpha_p^{\pi}\, \pi_{t-p} + \beta y_{t-1} + \gamma \Delta_4 RER_t + e_t^1, \tag{3}$$

$$\pi_{t+h} = c + \sum_{p=1}^{4} \alpha_p^{\pi}\, \pi_{t-p} + \beta \Delta_4 y_{t-1} + \gamma \Delta_4 RER_t + e_t^2, \tag{4}$$

$$\pi_{t+h} = c + \alpha_{exp}^{\pi} E_t \pi_{t+4} + \sum_{p=1}^{4} \alpha_p^{\pi}\, \pi_{t-p} + \beta \Delta_4 y_{t-1} + \gamma \Delta_4 RER_t + e_t^3, \tag{5}$$

where, $\pi_{t+h} = \log\left(\frac{P_{t+h}}{P_{t-4}}\right) - \pi_t^*$ denotes annual inflation expected *h* periods ahead minus the inflation target and P_t represents consumption price indices. We focus on several core price aggregates mentioned in Section II, therefore a constant is added to control for any mean effect remaining when switching to average inflation measures that are different from the target, e_t^1 , e_t^2 and e_t^3 are a iid.

error terms.[23] $E_t\pi_{t+j}$ denotes expectations of headline inflation j quarters ahead. The multilateral real exchange rate is denoted, RER_t and $\Delta_4 = 1 - L_4$ where L is the lag operator. The exercise consists of estimating (3) to (5) recursively with fixed size rolling windows. Note that the output gaps considered, y_{t-1}, are lagged one quarter and come from estimates in real-time, quasi-real time as well as staff output gap estimates.[24] Also, an AR(4) model is used as a benchmark forecasting model, since it emerges by restricting $\beta = \gamma = 0$ in equations (3) and (4), and $\beta = \gamma = \alpha_{exp}^{\pi} = 0$ in (5).

Tradable goods inflation represents a share of 40% in CPI inflation excluding food and energy reflecting the openness of Chile. Therefore, specifications (3) to (5) include exchange rate fluctuations as an additional control. We compared with most papers of the literature mentioned in this subsection and find that, in general, Phillips curve specifications omit exchange rates.[25] We believe that the specific choice of the regressor that tracks the marginal cost of imported goods is relevant to explain imported goods inflation.[26] Intuitively, that would be complementary to findings of a large literature that suggests that non-imported goods inflation are correlated with the output gap.

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[23] In the sample under analysis, inflation went down from two digit figures in the nineties to one digit in the period since 2001. Given this non-stationary behavior, to implement a feasible Phillips curve we stabilize the relevant inflation by defining inflation in deviations from the inflation target. Therefore, before 2001.Q2 we take observed inflation and subtract the time-varying yearly announced target. That period characterized by high inflation that gradually and steadily decreased, with capital controls and an operational real monetary policy instrument. The partial control exerted on the exchange rate by the authority was consistent with inflation target adjusting downwards. After, September 2001 the monetary policy rate instrument was nominal, with full flexibility of the exchange rate. Inflation target was set to three percent in a horizon period of two years. See Central Bank of Chile (2007). The Chilean case is interesting because in the last twenty years headline inflation averaged 3.1%, pretty close to the announced target of 3% set in 2001 and also two-year inflation expectations remained anchored. Therefore, we believe that substracting the inflation target from inflation does not underestimate credibility issues on target, at least in the subsample that starts in 2001 because the CB of Chile earned credibility by being succesfull in controlling inflation. García (2001) and Massad (2003) give an account of the policy implementation that leaded to earning credibity in the nineties, when the announced target had a downward trend.

[24] Why not use unemployment as alternative measure of slack? As stated in Section I, the unemployment rate is often subject to smaller revisions than GDP but comes with its own challenges and concerns, e.g labor hoarding behavior of firms in bad times, labor force participation issues, migration, etc. See Fleischman and Roberts (2011); Fernald *et al.* (2017).

[25] For the Chilean case, Pincheira and Rubio (2015) dismisses the exchange rate signal, while Fornero and Naudon (2016) include the lagged real exchange rate depreciation as an additional regressor.

[26] There are at least two alternative regressors to the real exchange rate depreciation. Firstly, fluctuations in the copper prices might be considered because the value of copper exports represent more than half of total Chilean exports. There is a statistically significant and negative correlation between the real exchange rate and real

We stated that the Chilean economy is exposed to significant foreign shocks and this would have implications for the identification of parameters of the Phillips curve. In effect, it is more difficult to estimate of its slope in small open and emerging economies in contrast with the (rather closed) US economy studied by Orphanides and van Norden.[27] To illustrate the case let us consider a recent episode. Very shortly after Bernanke's Tapering talk in May 2013, the dollar appreciated, copper prices started to go down, the Chilean peso depreciated against the US dollar by a sizable amount, shortly afterwards inflation and one year ahead expected inflation rose, and the output gap deteriorated.[28] As it is well known, any relative price change yields a trade off in setting monetary policy.

Therefore, the forecasting exercises proposed slightly differ from Orphanides and van Norden (2005) because we do not allow for model selection.[29] The reason is that in few subsamples, we noticed that applying mechanically information criteria for model selection could be misleading to trim model's structure because sometimes the preferred model lacks the output gap in the regressors' set. We believe that this is inconvenient and goes against the spirit of the Phillips curve, which have a measure of output gap (which is ultimately a proxy measure of the marginal cost).

For the forecasting exercises, we use output gaps calculated with: (i) real time data; (ii) with partial final data, i.e. quasi-real time; and (iii) final measures. We considered various rolling window (w) of

copper price (i.e. relative to a trade-wheighted foreign price index). Thus, given this stylized fact, we expect that our results are robust to this change. Secondly, fluctuations in import prices (unit import values in local currency) are appealing because are more linked to the true marginal cost of imported goods. However, that choice may exagerate the effects because of: (i) distribution costs are tied to sticky wages, which do not move much; and (ii) a fraction of the invoicing can be in a currency different than the US dollar. For the Chilean case, evidence suggests that about 90% of the invoicing is in US dollars, see Giuliano and Luttini (2019).

[27] In Chile, the policy framework favors full exchange rate flexibility coupled with independent monetary policy and responsible fiscal policy. These are key conditions that facilitate the shock absorber role of the exchange rate.

[28] The value of mining exports (mostly copper) as a share of total exports is close to 50% in last years, thus terms of trade shocks matter for Chile.

[29] We follow Champagne *et al.* (2018) maintaining invariant regressors in the specification. Orphanides and van Norden (2005) and Pichette *et al.* (2019) use standard statistical information criteria for model selection.

sizes: 28, 32, 36, 40, 60 and 80 quarters. Main results of the paper are generated setting $w = 60$.[30] [31] We study a set of core inflation measures: CPI excluding food and energy, median, common factor and trimmed-mean inflation. We also examined core non-tradable inflation and wage inflation, but to save space we reported results in Appendix D.

V.2 Forecasting inflation

This section presents main results of forecasting inflation exercises. First, in general for forecasting core inflation, the final staff output gap produces the lowest average forecast errors in comparison with other alternatives. In addition, the passage of the time is informative and sharpens the signal on the stance of the output gap in order to provide more accurate inflation forecasts. In other words, final staff's output gap estimates tend to be better in forecasting inflation in comparison with real time staff output gap information. Other filters such as HP yield similar results.

Second, considering quasi-real time output gaps, we find that these measures are as good as real time versions for forecasting inflation. In some common filters, differences are negligible as for instance in HP filters.

Third, due to the lack of flexibility, linear and quadratic deterministic filters provide poor forecasting performance of inflation. Besides, replacing the output gap by growth rates do not lead to significant improvements of the accuracy of forecasts.

[30] In addition, we ran recursive forecasting exercises, but to save space we do not report them. Results are very similar.

[31] Expanding on the previous footnote, a remark is that recursive forecasting exercises are risky in case of instability of parameters. To make the point clear, there is favorable evidence that the Phillips curve helped forecasting US inflation from the seventies until 1984, afterwards simpler models outperform the Phillips curve (Great Moderation period, Stock and Watson, 1999). The break of results also affects benchmark models (see Stock and Watson (2008)). In order to handle potential breaks, Fisher *et al.* (2002) conducts rolling window forecasting exercises with sample size of 60 quarters, as we do. Instability of parameters of various sources have been documented by Stock and Watson (1999, 2007), Clark and McCracken (2006), Dotsey and Stark (2005), Giacomini and Rossi (2009). We will touch on this issue in Section VI.

Fourth, adding inflation expectations in the specification help reducing the root mean square forecasts errors (RMSFE) of inflation other things constant. In addition, most of previous implications continue to hold, except that staff output gap performs better, but statistical significance vanishes.

Finally, as we examined the forecasting performance using various measures of core inflation; we find that previous results hold in general, are robust and RMSFE have comparable sizes. However, when applying statistical tests of predictive ability, slightly stronger evidence is obtained with median and common factor inflation measures. In these two cases, standard tests comparing RMSFE turn out to be more accurate to discriminate in favor of output gap staff measures.

The structure of Tables 6 and 7 is divided in two parts. On the left panel, each row reports average errors obtained by comparing realized inflation with forecasts resulting from Phillips curve models. For any method used to estimate the output gap, we report real-time and quasi-real measures. At the bottom of the table, we also provide final output gaps. Each column refers to the (quarter) forecasting horizon: 1, 2, 4, and 6. On the right panel, the same information is reported as ratios, taking as numeraire the RMSFE of inflation excluding food and energy using the output gap calculated by CBCh's staff. Therefore, numbers above one indicate a relatively lower performance in comparison with the predictive ability obtained with a similar model that observes the staff output gap. If the ratio is one, it means that both models yield on average equal forecasting errors: no winner emerges.

Beginning with the analysis of main results. First, for inflation excluding food and energy results provide a slight advantage for staff calculations over either the final, the real time or quasi-real time version at various forecasting horizons. However, it is quite difficult to make a firmer conclusion since evidence do not pass usual tests of statistical significance at 10 percent.[32]

Results turn out to be slightly better in favor of the staff output gap when considering median inflation, though results are similarly good when using trimmed-mean and common factor inflation. Three main

[32] Tables with *p*- values are available upon request.

results are worth highlighting. First, it emerges clearly that it is a bad idea to use deterministic trends to measure potential output for all forecasting horizons of inflation. This result is useful since before 2015 the staff of the CBCh used *trend* potential output to gauge the output gap. The problem with that approach is the lack of flexibility in the measure and the abundant uncertainty in the real use of inputs to calibrate the production function that determines the *trend* level. Second, forecasting errors arising from Phillips curves using HP, BP and BN filters are close competitors to staff output gap to forecast inflation in horizons within a year, while they perform poorly when $h > 4$ (again in comparison with staff output gap). Third, RMSFEs obtained with final measures of output gaps are not clearly better than CBCh's staff output gaps. Importantly, notice that these measures are —from the point of view of the policy maker— unfeasible.

Comparing Tables 6 and 7 it clearly appears that RMSFEs reported are lower for median inflation than for inflation excluding food and energy. In relative terms, average errors are more comparable in size. In Annex D, we report additional results covering alternative measures of inflation: non-tradable core inflation and wage inflation. In general, the main reason leaving this evidence in the annex is the lack of statistical significance in the results.

Table 8 reports more succinctly relative RMSFE gains for various core inflation measures (with respect to staff output gap calculations). CBCh's staff output gap in its final version seem to be better than real time in shorter forecasting horizons (shaded rows), while for $h = 6$ differences are statistically not significant. On the other side, more ratios are statistically significant and higher than staff. Notably, for $h = 4$ ratios are higher for all alternative measures of output gap, real time, quasi-real time and final. These last results are confirmed when $h = 6$. In summary, the CBCh's staff output gap provides a sharper signal for forecasting core inflation in comparison with alternatives. This finding is robust to various standard core inflation measures.

Table 6. Average forecasting errors. Inflation excluding food and energy (W=60)

Models	RMSFE				RMSE relative to Staff			
	h=1	*h*=2	*h*=4	*h*=6	*h*=1	*h*=2	*h*=4	*h*=6
AR(4)	0.63	1.11	1.76	1.77	1.00	1.04	1.05	**1.02**
HP RT	0.65	1.08	1.73	1.84	1.03	1.01	1.03	**1.06**
HP Quasi RT	0.66	1.09	1.76	1.80	**1.05**	1.02	1.05	1.04
BP RT	0.66	1.10	1.79	1.86	1.06	1.03	1.07	**1.07**
BP Quasi RT	0.68	1.12	1.79	1.84	**1.08**	1.05	1.07	**1.06**
BN RT	0.63	1.09	1.81	2.00	1.00	1.02	1.08	1.15
BN Quasi RT	0.63	1.11	1.86	1.97	1.01	1.03	1.11	1.14
LT RT	0.71	1.28	2.05	1.93	**1.13**	1.20	1.22	**1.11**
LT Quasi RT	0.70	1.25	2.02	1.92	**1.11**	1.17	1.20	**1.11**
QT RT	0.71	1.28	2.05	1.93	**1.13**	1.20	1.22	**1.11**
QT Quasi RT	0.70	1.25	2.02	1.92	**1.11**	1.17	1.20	**1.11**
Annualized Growth RT	0.63	1.09	1.73	1.87	1.01	1.02	**1.03**	**1.08**
Annual Growth RT	0.62	1.10	1.84	1.98	0.99	1.02	1.10	1.14
Annual Growth F	0.64	1.12	1.84	1.97	1.02	1.04	1.10	1.14
Staff	0.63	1.07	1.68	1.73	1.00	1.00	1.00	1.00
Staff F	0.61	1.00	1.64	1.77	0.97	0.93	**0.98**	1.02
HP F	0.61	0.97	1.57	1.69	0.97	0.91	0.94	0.97
BP F	0.65	1.03	1.64	1.77	1.04	0.96	0.98	1.02
BN F	0.64	1.11	1.86	1.97	1.02	1.04	1.11	1.14
LT F	0.68	1.20	1.94	1.88	1.09	1.12	1.16	**1.08**
QT F	0.68	1.20	1.94	1.88	1.09	1.12	1.16	**1.08**
Median filters F	0.65	1.11	1.86	1.88	1.04	1.04	1.11	1.08

Note: We used 43 periods to evaluate the means (2007.Q1 to 2018.Q1). Abbreviations: RT denotes real time, HP denotes Hodrick-Prescott filter, BP denotes Band Pass filter, BN Beveridge and Nelson filter (implemented following Kamber *et al.* 2018), LT (QT) linear (quadratic) deterministic trend, Staff F denotes staff final and Staff points to real time. HP F denotes final estimates using the HP filter. Similarly for other filter, such as BP, etc. On the bottom of the table we report the median of final filters. Ratios indicated in bold indicate statistical significance at the level of 0.1 using the test of Giacomini and White (2006).

Table 7. Average forecasting errors. Median inflation (W=60)

Models	RMSFE				RMSE relative to Staff			
	h=1	h=2	h=4	h=6	h=1	h=2	h=4	h=6
AR(4)	0.38	0.80	1.35	1.48	0.97	0.99	1.06	1.00
HP RT	0.39	0.78	1.34	1.61	0.99	0.98	**1.05**	**1.09**
HP Quasi RT	0.39	0.76	1.36	1.57	0.99	0.94	1.07	1.06
BP RT	0.41	0.80	1.38	1.56	1.03	1.00	**1.09**	**1.05**
BP Quasi RT	0.41	0.80	1.38	1.55	1.04	0.99	**1.09**	1.05
BN RT	0.39	0.80	1.42	1.76	0.98	1.00	**1.12**	**1.19**
BN Quasi RT	0.38	0.80	1.46	1.74	0.97	0.99	**1.15**	1.18
LT RT	0.45	0.95	1.65	1.77	**1.15**	**1.18**	**1.30**	**1.20**
LT Quasi RT	0.45	0.92	1.57	1.68	**1.14**	1.15	**1.24**	**1.13**
QT RT	0.45	0.95	1.65	1.77	**1.15**	**1.18**	**1.30**	**1.20**
QT Quasi RT	0.45	0.92	1.57	1.68	**1.14**	1.15	**1.24**	**1.13**
Annualized Growt	0.39	0.80	1.32	1.57	0.99	1.00	1.04	**1.07**
Annual Growth R	0.39	0.82	1.47	1.74	0.98	1.02	**1.15**	**1.18**
Annual Growth F	0.39	0.82	1.46	1.74	0.98	1.02	**1.15**	1.18
Staff	0.39	0.80	1.27	1.48	1.00	1.00	1.00	1.00
Staff F	0.34	0.65	1.17	1.50	**0.86**	0.80	0.92	1.01
HP F	0.35	0.67	1.18	1.44	**0.89**	0.83	0.93	0.98
BP F	0.37	0.71	1.21	1.51	**0.93**	0.88	0.95	1.02
BN F	0.39	0.80	1.47	1.74	0.98	1.00	**1.15**	**1.17**
LT F	0.44	0.91	1.56	1.70	**1.11**	1.13	**1.22**	1.15
QT F	0.44	0.91	1.56	1.70	**1.11**	1.13	**1.22**	1.15
Median filters F	0.39	0.80	1.47	1.70	0.98	1.00	1.15	1.15

Note: see note of previous table.

Table 8. Average forecasting errors relative to Staff of selected core inflations (W=60)

	RMSE relative to Staff											
Horizon (quarters)	h=2				h=4				h=6			
Core Inflation	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common
AR(4)	1.04	0.99	0.96	1.22	1.05	1.06	0.98	1.24	1.02	1.00	0.97	1.11
HP RT	1.01	0.98	1.01	1.19	**1.03**	1.05	**1.08**	**1.16**	1.06	**1.09**	1.10	**1.14**
HP Quasi RT	1.02	0.94	0.98	1.14	**1.05**	1.07	**1.09**	**1.17**	**1.04**	**1.06**	1.08	**1.14**
BP RT	1.03	1.00	1.07	1.24	1.07	**1.09**	**1.15**	**1.16**	**1.07**	1.05	**1.11**	**1.12**
BP Quasi RT	1.05	0.99	1.04	1.21	1.07	**1.09**	**1.11**	**1.15**	**1.06**	**1.05**	**1.08**	**1.13**
BN RT	1.02	1.00	1.00	1.11	**1.08**	**1.12**	**1.11**	**1.13**	**1.15**	1.19	**1.20**	1.08
BN Quasi RT	1.03	0.99	0.99	1.04	**1.11**	**1.15**	**1.11**	**1.10**	**1.14**	1.18	**1.15**	**1.07**
LT RT	1.20	**1.18**	1.16	**1.40**	1.22	1.30	1.26	1.35	1.11	1.20	1.28	1.09
LT Quasi RT	1.17	1.15	1.12	**1.36**	1.20	1.24	1.18	1.32	1.11	1.13	1.20	1.07
QT RT	1.20	**1.18**	1.16	**1.40**	1.22	1.30	1.26	1.35	1.11	1.20	1.28	1.09
QT Quasi RT	1.17	1.15	1.12	**1.36**	1.20	1.24	1.18	1.32	1.11	1.13	1.20	1.07
Annualized Growth RT	1.02	1.00	0.98	1.27	1.03	**1.04**	**1.00**	**1.24**	**1.08**	1.07	**1.06**	**1.10**
Annual Growth RT	1.02	1.02	1.04	1.08	**1.10**	**1.15**	**1.13**	**1.16**	**1.14**	**1.18**	**1.17**	1.06
Annual Growth F	1.04	1.02	1.03	1.01	**1.10**	**1.15**	**1.10**	**1.12**	**1.14**	**1.18**	**1.13**	**1.07**
Staff	1	1	1	1	1	1	1	1	1	1	1	1
Staff F	0.93	0.80	0.91	0.90	0.98	**0.92**	1.00	1.01	1.02	1.01	1.04	1.08
HP F	0.91	0.83	0.90	0.85	0.94	0.93	0.97	0.96	0.97	0.98	1.00	**1.05**
BP F	0.96	0.88	**0.94**	0.94	0.98	0.95	1.00	1.02	**1.02**	1.02	1.05	**1.10**
BN F	1.04	1.00	1.00	1.04	**1.11**	**1.15**	**1.11**	**1.10**	**1.14**	1.17	1.16	**1.07**
LT F	1.12	1.13	1.07	1.25	1.16	**1.22**	1.16	**1.22**	1.08	**1.15**	1.19	1.07
QT F	1.12	1.13	1.07	1.25	1.16	**1.22**	1.16	**1.22**	1.08	**1.15**	1.19	1.07
Median filters F	1.04	1.00	1.00	1.04	1.11	1.15	1.11	1.10	1.08	1.15	1.16	1.07

Note: see note to Table 6.

So far, results analyzed come from backward looking Phillips curves, as it is commonly done in the existing literature. However, in the macro literature most (DSGE or semi-structural gap) models used by central banks include expectations of inflation in the Phillips curve. That is motivated by the fact that when changing current goods prices forward looking agents will consider expected future marginal costs.

More in general, expectations are endogenous to the policy framework as well to the specific structure of the model. First, under inflation targeting a credible Central Bank sets its monetary policy with the objective that expected inflation tends to the target previously announced to the public. If agents believe that this is serious commitment, then expectations of inflation should be anchored around that target: in Chile, expected two-year ahead inflation is most of the time around three percent. In this way, one-year ahead expectations should be consistent with two-year ahead inflation expectations, they are not free. Second, for simplicity we used solely the Phillips curve to forecast inflation, which assumes exogeneity of independent variables. In the empirical implementation, we choose lags of explanatory variables to predetermine them as a way to alleviate the endogeneity problem. An alternative strategy is to write a model in which inflation dynamics is given by a Phillips curve where variables, which appear in the right hand side, are either determined within the model or are exogenous. An sketch of such a model's structure at least includes the following equations: an IS curve that describes the dynamics of the output gap in the business cycle frequency, a Phillips curve similar to (5) to explain inflation dynamics, a UIP condition to endogenize exchange rates dynamics (given a law of motion of foreign inflation), and a reaction function such as a Taylor rule describing the reaction of the Central Bank to inflation and output gap. We leave this for future work, but we remark that in a setting like this, inflation expectations are endogenously formed in the model.

We turn to the question of whether the addition of expectations in the Phillips curve help to lower average forecasts errors. The strategy is to conduct forecasting exercises with equation (5), using one year ahead inflation expectations.[33]

To begin with, Table 9 reports RMSFE for forecasting inflation excluding food and energy for different forecasting horizons using expectations obtained from the forecasting process conducted at the CBCh by the staff (MPRs). We find that RMSFE for each horizon considered do not change much in comparison with RMSFE resulting of using EEE (the abbreviation in Spanish of survey of professional forecasters). For horizon h = 1 or 2 (short run) historical MPRs' forecasts yield slightly smaller RMSFE, but in medium term results are quite similar. In particular, these differences seem to be not statistically significant. In Annex D, Table D3 we report results using EEE.

Overall, analyzing RMSFE results it is clear that the usage of expectations helps to improve forecasts errors other things equal. The evidence for supporting that statement comes from two direct comparisons: (i) RMSFE of columns 2 to 5 of Tables 6 and 9 and (ii) RMSFE columns 2 to 5 of Table 6. Major gains are found in shorter forecasting horizons such as one and two quarters. Other important results summarized at the beginning of this section remain when using expectations in the Phillips curve.

Finally, Tables 10 and 11 provide RMSFE relative to Staff's output gap for four measures of core inflation. The evidence expressed in ratios in Table 11 slightly favors Staff's inflation expectations over EEE survey (i.e., ratios are lower in Table 11). Additional results are worth mentioning. First, notice that results summarized at the beginning of this section continue to hold; especially, the evidence point to the fact that alternative (simple filters) output gaps lead to higher forecast errors of core inflation in comparison with staff calculations, though in some cases these differences are not statistically significant at 10% level. Second, our findings are relatively robust with comparable ratio

[33] Notice that the exercise uses conditional expectations made with information available at the moment of making the forecasts, mitigating the endogeneity problem that otherwise would arise by using future inflation.

sizes. However, it is interesting to that most significant RMSFE ratios correspond to median, trimmed mean and common inflation measures, suggesting that inflation of certain components is very hard to predict, thus excluding them improves forecasts from Phillips curves. Regarding the usual inflation measure that excludes food and energy components, results of RMSFE are of similar order of magnitude, but due to its volatility tests in the short run cannot discriminate on which measure of output gaps perform better (columns 2 and 6 of Tables 10 and 11). Finally, making a direct comparison of results from Table 8 with either Tables 10 or 11, we can learn the direction of change of RMSFE ratios with respect to Staff when including inflation expectations in the specification. Maintaining fixed the forecasting horizon; we find that differences are not sizeable in favor of the specification that includes inflation expectations, except for forecasting common factor inflation. For this particular measure including inflation, expectations prevent RMSFE ratios from rising when *h* enlarges.

Table 9. Average forecasting errors. Inflation excluding food and energy (W=60)

Monetary Policy Report inflation forecasts used in equation (5)

Models	RMSFE				RMSE relative to Staff			
	h=1	*h*=2	*h*=4	*h*=6	*h*=1	*h*=2	*h*=4	*h*=6
AR(4)	0.58	1.11	1.88	1.75	1.01	1.05	1.06	**1.04**
HP RT	0.60	1.06	1.78	1.78	1.03	1.01	1.01	1.06
HP Quasi RT	0.61	1.08	1.81	1.73	**1.05**	1.02	1.03	1.03
BP RT	0.62	1.09	1.79	1.82	1.06	1.03	**1.01**	**1.08**
BP Quasi RT	0.63	1.10	1.80	1.79	**1.08**	1.04	1.02	1.06
BN RT	0.58	1.08	1.90	1.96	1.01	1.03	1.07	1.16
BN Quasi RT	0.60	1.12	1.93	1.92	1.04	1.06	1.09	1.14
LT RT	0.63	1.23	2.13	1.96	**1.09**	1.17	1.20	1.16
LT Quasi RT	0.64	1.23	2.10	1.92	**1.11**	1.17	1.19	1.14
QT RT	0.63	1.23	2.13	1.96	**1.09**	1.17	1.20	1.16
QT Quasi RT	0.64	1.23	2.10	1.92	**1.11**	1.17	1.19	1.14
Annualized Growth RT	0.58	1.08	1.83	1.86	1.01	1.02	**1.03**	**1.10**
Annual Growth RT	0.57	1.08	1.91	1.94	0.99	1.02	1.08	1.15
Annual Growth F	0.60	1.11	1.92	1.93	1.04	1.05	1.08	1.14
Staff	0.58	1.06	1.77	1.69	1.00	1.00	1.00	1.00
Staff F	0.58	1.00	1.66	1.68	1.00	0.94	0.94	0.99
HP F	0.57	0.98	1.64	1.62	0.99	0.93	0.93	**0.96**
BP F	0.63	1.03	1.64	1.69	1.08	0.97	0.93	1.00
BN F	0.61	1.12	1.93	1.92	1.04	1.06	1.09	1.14
LT F	0.62	1.18	2.04	1.88	1.08	1.12	1.16	**1.11**
QT F	0.62	1.18	2.04	1.88	1.08	1.12	1.16	**1.11**
Median filters F	0.62	1.12	1.93	1.88	1.08	1.06	1.09	1.11

Note: see note to Table 6.

Table 10. Average forecasting errors relative to Staff of selected core inflations (W=60)

Survey of Professional Forecasters (EEE) used in equation (5)

	RMSE relative to Staff											
Horizon (quarters)	*h*=2				*h*=4				*h*=6			
Core Inflation	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common
AR(4)	1.06	0.98	0.97	1.19	1.04	1.06	0.99	1.29	1.03	1.03	0.98	1.26
HP RT	1.01	1.00	1.04	1.20	**1.01**	1.02	**1.05**	**1.18**	1.04	**1.08**	1.09	**1.19**
HP Quasi RT	1.03	0.98	1.02	1.15	**1.03**	1.05	**1.07**	**1.19**	**1.03**	**1.07**	1.08	**1.19**
BP RT	1.04	1.02	1.10	1.27	1.02	**1.05**	**1.10**	**1.20**	**1.07**	1.08	**1.12**	**1.15**
BP Quasi RT	1.05	1.02	1.07	1.22	1.02	**1.06**	**1.08**	**1.17**	**1.06**	**1.08**	**1.10**	**1.17**
BN RT	1.06	1.02	1.03	1.11	**1.09**	**1.11**	**1.10**	**1.17**	**1.15**	1.19	**1.22**	1.18
BN Quasi RT	1.10	1.02	1.03	1.04	**1.12**	**1.14**	**1.11**	**1.13**	**1.14**	1.19	**1.20**	**1.15**
LT RT	1.13	**1.09**	1.10	**1.26**	1.18	1.24	1.21	1.35	1.18	1.26	1.32	1.32
LT Quasi RT	1.15	1.08	1.08	**1.26**	1.18	1.19	1.15	1.33	1.14	1.19	1.22	1.26
QT RT	1.13	**1.09**	1.10	**1.26**	1.18	1.24	1.21	1.35	1.18	1.26	1.32	1.32
QT Quasi RT	1.15	1.08	1.08	**1.26**	1.18	1.19	1.15	1.33	1.14	1.19	1.22	1.26
Annualized Growth RT	1.03	0.99	0.99	1.24	1.05	**1.03**	**1.00**	**1.29**	**1.11**	1.13	**1.12**	**1.27**
Annual Growth RT	1.03	1.01	1.04	1.08	**1.09**	**1.13**	**1.13**	**1.18**	**1.15**	**1.19**	**1.23**	1.13
Annual Growth F	1.07	1.01	1.04	1.01	**1.10**	**1.13**	**1.11**	**1.13**	**1.14**	**1.21**	**1.20**	**1.14**
Staff	1	1	1	1	1	1	1	1	1	1	1	1
Staff F	0.95	0.86	0.96	0.88	0.94	**0.91**	0.97	0.98	0.99	1.00	1.01	1.06
HP F	0.94	0.86	0.95	0.86	0.94	0.94	0.97	0.97	0.96	1.00	1.00	**1.07**
BP F	0.99	0.93	**1.01**	0.94	0.93	0.93	0.96	1.03	**1.00**	1.02	1.02	**1.12**
BN F	1.10	1.02	1.03	1.04	**1.12**	**1.15**	**1.12**	**1.13**	**1.14**	1.19	1.20	**1.15**
LT F	1.11	1.09	1.07	1.21	1.14	**1.19**	1.14	**1.25**	1.12	**1.17**	1.20	1.24
QT F	1.11	1.09	1.07	1.21	1.14	**1.19**	1.14	**1.25**	1.12	**1.17**	1.20	1.24
Median filters F	1.10	1.02	1.03	1.04	1.12	1.15	1.12	1.13	1.12	1.17	1.20	1.15

Note: see note to Table 6.

Table 11. Average forecasting errors relative to Staff of selected core inflations (W=60)

Monetary Policy Report inflation forecasts used in equation (5)

	RMSE relative to Staff											
Horizon (quarters)	*h*=2				*h*=4				*h*=6			
Core Inflation	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common	Non food & energy	Median	Trimmed mean	Common
AR(4)	1.05	0.97	0.96	1.19	1.06	1.09	1.01	1.27	1.04	1.05	1.00	1.20
HP RT	1.01	0.96	1.00	1.18	**1.01**	1.01	**1.05**	**1.17**	1.06	**1.08**	1.09	**1.16**
HP Quasi RT	1.02	0.95	1.00	1.14	**1.03**	1.03	**1.05**	**1.18**	**1.03**	**1.04**	1.06	**1.14**
BP RT	1.03	1.00	1.07	1.24	1.01	**1.02**	**1.07**	**1.16**	**1.08**	1.07	**1.11**	**1.12**
BP Quasi RT	1.04	1.00	1.04	1.21	1.02	**1.04**	**1.05**	**1.15**	**1.06**	**1.06**	**1.08**	**1.14**
BN RT	1.03	1.00	1.00	1.09	**1.07**	**1.09**	**1.09**	**1.13**	**1.16**	1.19	**1.20**	1.13
BN Quasi RT	1.06	1.01	1.02	1.05	**1.09**	**1.12**	**1.08**	**1.11**	**1.14**	1.16	**1.16**	**1.10**
LT RT	1.17	**1.12**	1.12	**1.26**	1.20	1.24	1.19	1.31	1.16	1.24	1.29	1.20
LT Quasi RT	1.17	1.10	1.08	**1.26**	1.19	1.19	1.14	1.30	1.14	1.17	1.21	1.17
QT RT	1.17	**1.12**	1.12	**1.26**	1.20	1.24	1.19	1.31	1.16	1.24	1.29	1.20
QT Quasi RT	1.17	1.10	1.08	**1.26**	1.19	1.19	1.14	1.30	1.14	1.17	1.21	1.17
Annualized Growth RT	1.02	0.98	0.98	1.25	1.03	**1.00**	**0.98**	**1.23**	**1.10**	1.10	**1.09**	**1.18**
Annual Growth RT	1.02	1.02	1.04	1.08	**1.08**	**1.13**	**1.11**	**1.16**	**1.15**	**1.17**	**1.18**	1.09
Annual Growth F	1.05	1.02	1.04	1.02	**1.08**	**1.12**	**1.09**	**1.12**	**1.14**	**1.17**	**1.16**	**1.09**
Staff	1	1	1	1	1	1	1	1	1	1	1	1
Staff F	0.94	0.84	0.95	0.90	0.94	**0.90**	0.97	1.00	0.99	0.98	1.00	1.06
HP F	0.93	0.84	0.93	0.86	0.93	0.93	0.96	0.97	0.96	0.96	0.98	**1.04**
BP F	0.97	0.91	**0.98**	0.94	0.93	0.92	0.95	1.02	**1.00**	0.99	1.01	**1.10**
BN F	1.06	1.01	1.02	1.04	**1.09**	**1.12**	**1.09**	**1.10**	**1.14**	1.16	1.16	**1.10**
LT F	1.12	1.09	1.06	1.19	1.16	**1.20**	1.14	**1.23**	1.11	**1.17**	1.19	1.15
QT F	1.12	1.09	1.06	1.19	1.16	**1.20**	1.14	**1.23**	1.11	**1.17**	1.19	1.15
Median filters F	1.06	1.01	1.02	1.04	1.09	1.12	1.09	1.10	1.11	1.16	1.16	1.10

Note: see note to Table 6.

VI. Estimating output gap coefficients in the Phillips curve

We now turn to some related results. Regarding the question whether the real time measures give a better signal of the output gap in comparison with quasi-real time output gap measures, the literature suggests that there is no systematic gain in using real time measures to predict inflation (Orphanides and van Norden, 2005). Our findings reported in the previous section seem to confirm those results. In view of the evidence of Table 11, final measures of filters seem to perform better than real time and quasi-real time measures. More importantly, evidence suggests that real time measures do not make a real difference in forecasting inflation. Why? Although, many reasons may be competing to explain this, we highlight in Figure 3 the fact that estimated output gap coefficients seem to be relatively similar in size and in its evolution. In addition, estimated coefficients of real time measures are slightly more volatile. For example, the relative volatility of the estimates using the HP filter, namely $\sigma_\beta\ (HPRT)/\ \sigma_\beta\ (HPQuasiRT)$ is equal to 1.22, while this ratio is closer to 1 when considering deterministic linear trends (results are similar for quadratic trends, around 1.04). This is not surprising because of the higher volatility of the RT output gap measures. The particular jump or instability of staff output gaps' estimated coefficients by September 2015 is due to the methodological change that took place, namely standard production function methods were replaced by multivariate filters (see Annex A for further details).

Rossi (2013) surveys the literature that focuses on forecasting with instabilities in general. This paper is relevant because considers a similar setting studied by us building upon previous work by Stock and Watson (1996, 2003). The empirical literature confronts with two broad issues related to our paper: (i) in sample, the Phillips curve relationship seems to be episodic, with periods in which it fits well the data and other periods where it does not; (ii) regarding the relationship between in-sample fit and out-of-sample forecasting ability, the researcher is interested in identifying regressors capable of being good predictors, using standard hypotheses tests. The issue at hand is that due to autocorrelation of residuals, typical HAC corrections diminish the ability of the test to reject the null of no effect. In other words, the larger volatility of real time output gap elasticities mines the power of the t-test to reject the null of no effect.

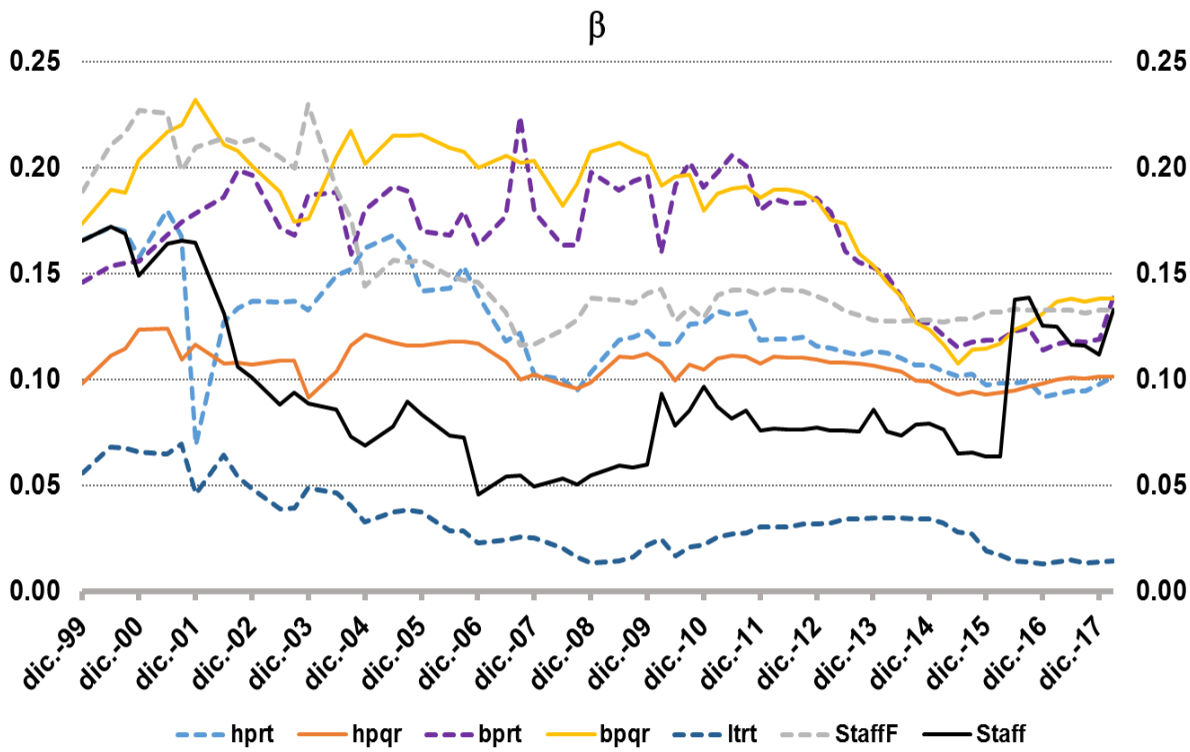
In addition, in periods that are more recent we observe a systematic lowering of coefficient estimates coherent with evidence of flattening of the Phillips curve.[34] In particular, slope estimated coefficients after 2014 for all real time and quasi-real output gap measures considered. As a benchmark, we also report estimates using final staff output gap measures, which are rather more stable. Notably, this finding is robust if we use either real time or quasi-real time output gap measures (left and right panel of the figure). This evidence is also robust if we use a window length of 40 quarters or 80 quarters; however, this is not reported to save space.

The flattening has been scarcely studied for small open economies. For example, Szafranek (2017) finds evidence of flattening for Poland, Çiçek (2012) reports similar results for Turkey. The hypothesis investigated point to global drivers, which have had a negative effect on domestic inflation rates.

Finally, these empirical findings can be interpreted with theoretical macroeconomic models. As Dotsey *et al.* (2018) points out, the paper by Benigno and Ricci (2011) features downward nominal wage rigidities in an otherwise standard stochastic general equilibrium model. Under standard assumptions, the model is capable of providing predictions in line with the flattening of the Phillips curve as long as volatility of shocks drops and remains low.

[34] Several studies suggest a flattening of the Phillips curve for developed countries.

Figure 3: Phillips curve output gap coefficients, inflation excluding food and energy (W=60)



Note: hpqr denotes HP filter Quasi-real time, bp denotes Band Pass filter lt linear deterministic trend, and StaffF denotes staff final and Staff is real time.

VII. Conclusions

The paper examines the informational properties of output gap revisions for Chile and use them to analyze implications for forecasting inflation using the Phillips curves. Despite most of the literature has focused on advanced economies, there is very little evidence for developing small open economies, such as the case of Chile.

It is common to derive measures of slack in the economy from either the labor market or economic output. These macroeconomic variables are usually, and sometimes substantially, revised. First, we examine whether output gap revisions are well behaved, namely they have zero mean, they are small and unpredictable, which means that provisional estimates can be regarded as an efficient forecast of the final series and subsequent revisions reduce the forecast error by incorporating new information.

In line with previous literature for output gap and other macroeconomic variables, we find that the unconditional mean of Chilean output gap revisions is positively biased, although not statistically significant when using a consistent filter to calculate it. When identifying the sources of revisions, we find that the main sources of staff's benchmark corrected revisions are methodological changes and data corrections, explaining around 78% and 20% of the mean of total revisions, respectively, using an HP filter as benchmark methodology. We also report a relatively large variance of revisions compared to the original output gap series —especially when using the HP or BP filter— with a high noise-to-signal ratio. It is worth mentioning that for staff's benchmark corrected revisions, although the mean of revisions is positive and statistically significant —in contrast to using an HP filter— the variance of revisions is heavily reduced compared to standard filters calculations.

Further evidence arises by testing the predictability of revisions. Our findings show that although past revisions are statistically significant when estimating final revisions, a random walk has overall lower RMSE than the models including past revisions. These results for output gap revisions indicate that despite they are positive and of a significant size, they are unpredictable and they eliminate the forecast error by incorporating relevant "news".

Second, we conduct forecasting exercises with Phillips curves using various measures of output gaps: real time, quasi-real time and final. We consider output gaps calculated with standard statistical methods as well as a new dataset that collects output gaps from the various Monetary Policy Reports issued by the CBCh. We examined backward- and forward-looking specifications of Phillips curves as the later can be implemented with historical forecasts of inflation available from various Monetary Policy Reports. The results are summarized as follows: the mere passage of time is informative to measure the output gap: inflation forecasts using final estimates of output gaps provide lower forecasting errors (everything else constant); forward looking specifications are slightly more useful to forecast inflation; and, finally, staff output gap calculations favorably compares with several alternatives, in terms of inflation forecasting accuracy. Results are robust. Median inflation and common factor inflation yield smaller forecast errors among core inflations considered. Finally, we find some evidence of the flattening of the Phillips curve, although this is not linked to either the real time or final estimates of the output gap.

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Annex A

Since the first Monetary Policy (MP) Report of May 2000 until the present, the staff of the Central Bank of Chile has upgraded estimation methodologies to infer the potential output level and consequently the output gap. While internally documented, these changes were not all published.[35] To fill this gap, we briefly describe major methodological upgrades as follows:

1. MP Reports from May 2000 to September 2004 used the Hodrick-Prescott filter on GDP to obtain trend estimates. Output gaps were hardly ever communicated. In the MP Report of May 2003 several output gap measures were discussed in the international context (Box IV.1). In particular, in the forecasting process the focus shifted on a measure of core GDP constructed as GDP excluding mining sector, fishing and electricity gas and water (GDP rest), but this output measure was not used to infer the trend output level neither the output gap. In Chile the methodology were under investigation and development at that time; see for instance, Gallego and Johnson (2001), Contreras and García (2002), Chumacero and Gallego (2002).
2. MP Reports from May 2005 to June 2015 implemented the production function approach. That choice resulted in further demands to dig deeper in the analysis and measurement of determinants of trend output measure. Naturally, the implementation led to measurement issues to better reflect contributions of labor, capital as well as productivity to trend GDP levels.[36] We highlight a selection of main upgrades that, ultimately, reflected challenges and/or issues of internal discussion at the CBCh:
    a. MP Report of May 2005 introduced several improvements (see Box IV.3). The TFP started to be filtered to avoid introducing cyclicality into the inference of the instance of trend TFP and output measure.[37] Besides, it incorporated a separation of labor participation of men and women and corrected the labor input by effective productivity (proxied by years of education). In addition, there were changes in quarterly national accounts (Box IV.1).
    b. MP Report of May 2007 incorporated methodological changes in National Accounts data: the 1996 base year is replaced by year 2003. That triggered reestimation of trend GDP, labor unit costs, and various models' elasticities. However, since official

[35] The output gap is a crucial input in the MEP model, a model written in gaps (Central Bank of Chile, 2003).
[36] All production inputs such as labor and capital were adjusted to reflect efficiency levels of usage, consistent with full employment.
[37] The Hodrick-Prescott filter used a $\lambda = 10000$ to avoid trend TFP to be influenced by cyclical behavior.

capital data series were not updated until April 2008, the estimation of trend output remained the best available, but provisional.

c. MP Report of September 2008. The trend output measure was estimated with full consistency with official capital measures by Henriquez (2008).

d. MP Report of May 2009. The following discussion of the depressing effects of increases of energy prices on productivity and on trend GDP was suggested in the MP Report of September 2008 (Box V.2). The issue was analyzed and discussed internally using different calibrations of production functions where the energy had a role in the production. Finally, using results from regressions, the TFP was downward adjusted in the forecast.

e. The production function methodology used yielded the level of the trend output gap not determined. The assumption was to set a constant so that the level yields an output gap for the year 1994 on average equal to zero (this assumption is based on conclusion of some literature that suggested that a macroeconomic equilibrium was reached in the year 1994, see Fuentes *et al.* (2008) p.14 and Contreras and García (2002)). This particular assumption was shared with other methodologies used at the CB of Chile to estimate key unobserved variables, such as equilibrium RER (see e.g. Caputo and Nuñez 2008), among others. In the MP Report of December 2014, the assumption that the output gap (GDP rest) was zero in 1994 was phase out. A new assumption resulted in an output gap time-series that averages zero in the sample (to get that result, an adjustment in the constant did the job in the trend output level). This upgrade allowed: (i) to enlarge the set of benchmark methodologies to estimate output gaps and to make meaningful comparisons (e.g. statistical filters assume in sample output gap equal to zero), (ii) to shorten the sample period of estimation to gain homogeneity, the natural choice is the inflation target period implemented with a nominal interest policy rate (from 2001:Q3 onwards).

3. MP Reports from September 2015 to June 2018 (the last MP Report in our sample). Albagli and Naudon (2015) made explicit the conceptual separation of trend and potential GDP. Trend GDP continued to be estimated using the production function approach (Albagli *et al.* 2015b). Regarding the methodology used to estimate potential GDP, we used versions of multivariate filters (Albagli *et al.* 2015a). Since the MP report of September 2016, the official potential output estimate is an average of two multivariate filters: (i) a Tri-variate filter that assumes an IS curve affected by the real rate, a Phillips curve and an Euler equation, where neutral interest rate is a function of potential output growth (see Fuentes *et al.*, 2008); (ii) a

multivariate filter with open economy effects in inflation in the Phillips curve [Albagli *et al.* (2015b) extended the closed economy case proposed by Blagrave *et al.* (2015)]. In particular, the simple average of output gaps from both filters provided lower forecast error of inflation in standard out-of-sample exercises.

4. Lastly, the MP Report of September 2018 replaced the GDP rest with non-mining GDP as a key measure of output gap (See Fuentes *et al.* (2018) and Bullano *et al.*, 2018).[38] That means that our sample can be enlarged since the GDP rest output gap is discontinued since that MP Report.

The changes referred above are intended to make more transparent the context, the learning process and the refinement of the methods used at the CBCh. However, for the purpose of this paper, notice that there is a trade-off between longer output gap revisions and data comparability. In effect, data is more comparable when more methodological adjustments are taken into account; however, since only data generated with the same estimation methodology is compared, the cost of incorporating many adjustments is to rule out the possibility of considering longer revisions. Therefore, we identify the following methodological changes:

MP Report September 2008

MP Report December 2014

MP Report September 2015

[38] The CBCh does not publish the output gap on regular basis. Since 2015 onwards, the output gap is published in the MP report of September.

Annex B

Table B1 reports the summary statistics for output and potential output; for each variable, we count with around 70 quarterly observations, about 17 years of data. Statistics are calculated for different horizons of revision, from one quarter revision ($r_{t,1}^{\widehat{GDP}}$) up to two years revision ($r_{t,8}^{\widehat{GDP}}$), and also the final revision ($r_{t,f}^{\widehat{GDP}}$) and the final revision after controlling by benchmark revisions (${r_{t,f}^{BR}}^{\widehat{GDP}}$).

Output

Beginning with revisions' first moments, means of annual growth of output from 1 year revisions forward, result to be significant and relatively stable around 0.23 (first row of Table B1).[39] For final revisions, the mean increases to 0.57, however after controlling by benchmark revisions this value is reduced to 0.30. These values are roughly similar to those found by Aruoba (2008) for the US economy. Using annualized quarterly growth, results indicate positive means; however, they are statistically not different from zero. Further examination of absolute means of revisions, confirm previous results suggesting that around ¾ of the total revision of output is made within the first and a half year, and there is only marginal revision after two years form the initial announcement. Besides, minimum and maximum revisions maintain relatively stable across time horizons of revisions, and they are of a magnitude similar to the values reported by Aruoba (2008).

Continuing with revisions' second moments the general finding is that the standard deviation is increasing with the horizon of revisions, as expected, with a much higher deviation when using annualized quarterly growth. Another measure to assess the size of revisions relative to the original variable is the noise-to-signal ratio, which is defined as the standard deviation of revisions divided by the standard deviation of the final value of the output. The ratio for output final revisions is 0.23 when using annual growth and 0.48 when using quarterly growth, this ratio is steady from revisions from 1½ year forward.

To test the noise versus news hypothesis firstly proposed by Mankiw and Shapiro (1984), the correlation of revisions with the initial announcement and with the final values are reported. Results are generally not conclusive, only when using quarterly growth of output, a significant positive correlation is reported for output revisions from 1½ year forward. Finally, the last row of Table B1 reports the first order autocorrelation coefficients. For annual growth of output revisions from 1½-year forward, results indicate some persistence, with autocorrelation coefficients from 0.26 to 0.44.

[39] Following Aruoba (2008), we use Newey-West standard errors in computing the test of significance for the means of revisions.

Potential output

For potential output, the mean of revisions is generally negative and only statistically significant for revisions of annual growth from two quarters to two years revisions. One feature that is worth mentioning is that after controlling by benchmark revisions, the mean of the final revision is close to zero and not significant. In terms of absolute mean and standard deviation, the magnitude of final revisions is smaller than one or two year revisions. This can be explained due to the higher importance of the methodological changes to estimate potential output in the 17 years of sample.

The correlation of revisions is consistently negative with the initial announcement and positive with the final value, in both cases the coefficients are sizable and statistically significant. This means that potential output is correcting a bit each time towards the signal (data). In addition, the revisions of output gap growth seem to be positively autocorrelated and estimated coefficients are overall significant. Although lower than the values obtained by Aruoba – which were around 0.66 for output– the persistence of revisions could suggest that could be anticipated.

Formal evidence

Table B2 replicates the results of Aruoba (2008) estimating exercise for revisions of output and potential output. Although past revisions variables are altogether not significant to explain output revisions, the models that include them still have a smaller RMSE relative to a random walk model. For potential output, past revisions result statistically significant for almost all revision horizons, with higher r-squared statistics than for output revisions. Comparing with a random walk model, models including past revision have a higher RMSE when considering annual growth and smaller RMSE when considering quarterly growth of potential output. As in Aruoba (2008), past revisions are statistical significant when estimating output final revisions; moreover, models including past revisions have a lower RMSE than a random walk. However, none of these results maintain for potential output. In summary, results suggest that past revisions have a higher explanatory power to estimate potential output revisions than output revisions, for which past revisions seem to be not significant.

Table B1. Summary Statistics of Output and Potential Output Revisions

A. Real Output Revisions: $r_{t,i}^{\widehat{GDP}} \equiv \widehat{GDP}_{t,t+1+i} - \widehat{GDP}_{t,t+1}$

Statistic / Horizon i	1Q	2Q	1Y	1½Y	2Y	Final^{2018Q2}	Final^{BR}
Annual growth							
Mean	0.010	0.091	**0.230**	**0.229**	**0.248**	**0.566**	**0.297**
Absolute mean	0.230	0.364	0.509	0.660	0.618	0.944	0.664
Minimum	-1.389	-0.965	-1.542	-2.657	-2.250	-2.566	-1.955
Maximum	0.834	1.492	1.649	1.955	1.682	2.934	2.612
Standard Deviation	0.348	0.470	0.602	0.819	0.759	1.042	0.811
Noise-signal ratio	0.099	0.134	0.171	0.233	0.216	0.297	0.231
Correlation w/Initial	-0.149	-0.087	-0.052	0.127	0.029	0.051	-0.135
Correlation w/Final	-0.134	0.052	0.108	**0.325**	0.232	**0.444**	0.133
AR(1)	-0.010	0.145	0.155	**0.389**	**0.437**	**0.272**	**0.256**
Quarterly growth (annualized)							
Mean	0.207	-0.012	0.185	0.386	0.371	0.648	0.282
Absolute mean	1.012	1.387	1.649	2.199	2.197	2.635	2.148
Minimum	-4.667	-8.989	-7.418	-8.154	-8.289	-9.151	-6.134
Maximum	6.962	4.954	4.941	5.900	6.149	9.325	9.932
Standard Deviation	1.642	1.995	2.158	2.717	2.750	3.428	2.864
Noise-signal ratio	0.274	0.333	0.360	0.453	0.459	0.572	0.478
Correlation w/Initial	-0.192	**-0.286**	-0.183	-0.157	-0.155	**-0.334**	-0.179
Correlation w/Final	0.174	-0.008	0.103	**0.282**	**0.378**	**0.560**	**0.440**
AR(1)	0.088	-0.014	-0.019	-0.077	-0.029	-0.283	-0.227

B. Potential Output Revisions: $r_{t,i}^{\widehat{GDP}^{pot}} \equiv \widehat{GDP}_{t,t+1+i}^{pot} - \widehat{GDP}_{t,t+1}^{pot}$

Statistic / Horizon i	1Q	2Q	1Y	1½Y	2Y	Final^{2018Q2}	Final^{BR}
Annual growth							
Mean	-0.033	**-0.094**	**-0.177**	**-0.232**	**-0.267**	0.096	-0.026
Absolute mean	0.154	0.239	0.373	0.503	0.564	1.004	0.318
Minimum	-0.859	-1.062	-1.179	-1.557	-1.640	-1.755	-1.085
Maximum	0.988	1.114	1.114	1.013	1.542	3.019	1.441
Standard Deviation	0.262	0.344	0.446	0.562	0.649	1.247	0.419
Noise-signal ratio	0.213	0.279	0.362	0.456	0.526	1.011	0.340
Correlation w/Initial	-0.194	**-0.255**	**-0.337**	**-0.426**	**-0.475**	**-0.444**	-0.219
Correlation w/Final	0.237	**0.273**	**0.335**	**0.344**	**0.384**	**0.625**	0.211
AR(1)	0.198	**0.457**	**0.706**	**0.784**	**0.759**	**0.924**	**0.662**
Quarterly growth (annualized)							
Mean	0.009	-0.036	-0.146	-0.238	-0.227	0.119	-0.019
Absolute mean	0.339	0.484	0.609	0.766	0.811	1.218	0.552
Minimum	-2.545	-2.185	-1.851	-3.996	-1.768	-2.118	-2.106
Maximum	4.596	4.596	4.374	4.379	5.264	8.047	4.264
Standard Deviation	0.827	0.955	0.960	1.111	1.117	1.811	0.909
Noise-signal ratio	0.665	0.768	0.772	0.893	0.898	1.457	0.731
Correlation w/Initial	**-0.525**	**-0.667**	**-0.645**	**-0.669**	**-0.755**	**-0.737**	**-0.518**
Correlation w/Final	0.203	0.229	**0.325**	**0.290**	**0.340**	**0.535**	**0.259**
AR(1)	0.098	0.067	0.192	**0.241**	**0.403**	**0.664**	**0.312**

Source: Authors' elaboration.

Notes: Number of observations by horizon of revision: 1Q (73), 2Q (72), 1Y (70), 1½Y (68), 2Y (66) Final^{2018Q2} (74 for Real GDP and 63/66 for Potential GDP annual/quarterly growth), Final^{BR} (66).

Bold values indicate statistical significance at the level of 0.05.

GDP revision defined as: $r_{t,i}^{\widehat{GDP}} \equiv \widehat{GDP}_{t,t+1+i} - \widehat{GDP}_{t,t+1}$, where $\widehat{GDP}_t \equiv GDP_t - GDP_{t-i}$, with $i = 1$ for quarter growth and $i = 4$ for annual growth. Same for Potential GDP revisions ($r_{t,i}^{\widehat{GDP}^{pot}}$).

Table B2. Results of the Estimation Exercises for Potential GDP and GDP

Revision Horizon	Model 1 (revision variables)	Wald	R2	Adj. R2	RMSE1/ RMSE4	RMSE2/ RMSE4	RMSE3/ RMSE4
Output: Annual growth							
1 Quarter	Rev2y	0.077	0.173	0.088	0.677	0.676	0.704
1 Year	Rev1y	0.797	0.049	-0.047	0.756	0.796	0.775
2 Years	Rev1½y	0.342	0.114	0.016	0.837	0.970	0.942
$Final^{2018Q2}$	Rev1q – Rev1¼y	**0.003**	0.348	0.236	0.676	0.836	0.850
$Final^{BR}$	Rev18m	0.091	0.164	0.079	0.720	0.859	0.850
Output: Quarterly growth (annualized)							
1 Quarter	Rev1q	0.224	0.121	0.040	0.722	0.756	0.750
1 Year	Rev1q – Rev1½y	0.166	0.239	0.078	0.583	0.721	0.710
2 Years	Rev1q – Rev2y	0.059	0.357	0.168	0.576	0.714	0.710
$Final^{2018Q2}$	Rev1q – Rev1¾y	**0.009**	0.364	0.222	0.490	0.601	0.635
$Final^{BR}$	Rev1q – Rev2y	0.099	0.307	0.123	0.549	0.649	0.648
Potential Output: Annual growth							
1 Quarter	Rev1y	0.129	0.143	0.061	0.781	0.792	0.790
1 Year	Rev2y	**0.000**	0.407	0.343	1.011	1.262	1.306
2 Years	Rev2y	**0.000**	0.405	0.335	1.200	1.316	1.458
$Final^{2018Q2}$	Rev1q – Rev2y	**0.000**	0.859	0.821	1.111	1.513	2.631
$Final^{BR}$	Rev2y	**0.023**	0.223	0.140	1.045	1.229	1.223
Potential Output: Quarterly growth (annualized)							
1 Quarter	Rev1q – Rev1¾y	**0.001**	0.453	0.329	0.642	0.643	0.744
1 Year	Rev1q – Rev2y	**0.000**	0.672	0.583	0.524	0.612	0.787
2 Years	Rev1q – Rev2y	**0.000**	0.780	0.715	0.499	0.615	0.916
$Final^{2018Q2}$	Rev1q – Rev2y	**0.000**	0.956	0.945	0.285	0.547	1.220
$Final^{BR}$	Rev1q – Rev1y	**0.000**	0.541	0.469	0.598	0.729	0.851

Source: Authors' elaboration.
Note: Bold values indicate statistical significance at the level of 0.05.
Model 1 includes constant, initial announcement, trend and seasonal dummies.

Annex C

Table C1. Output Gap Revisions Summary Statistics

A. Output Gap Revisions: Staff estimations $r_{t,i} \equiv y_{t,t+1+i} - y_{t,t+1}$

Statistic / Horizon i	1Q	2Q	1Y	1½Y	2Y	Final^{2018Q2}	Final^{BR}
Mean	**0.173**	**0.310**	**0.595**	**0.826**	**1.169**	**1.394**	**0.492**
Absolute mean	0.327	0.650	0.953	1.281	1.413	1.541	0.656
Minimum	-1.230	-3.059	-4.079	-4.507	-1.466	-1.348	-1.389
Maximum	1.694	2.307	3.984	4.106	3.979	3.949	2.911
Standard Deviation	0.476	0.855	1.236	1.514	1.415	1.323	0.694
Noise-signal ratio	0.291	0.522	0.754	0.923	0.863	0.807	0.423
Correlation w/Initial	-0.026	-0.003	0.061	0.133	0.221	**-0.646**	-0.049
Correlation w/Final	0.103	**0.252**	**0.385**	**0.478**	**0.486**	-0.038	**0.261**
AR(1)	0.021	**0.493**	**0.630**	**0.643**	**0.720**	**0.831**	**0.287**

B. Output Gap Revisions: Using HP Filter.

	Real ($r_{t,i}^{HP}$)			Quasi-real ($r_{t,i}^{Q,HP}$)		
Statistic / Horizon i	1Y	2Y	Final^{2018Q2}	1Y	2Y	Final^{2018Q2}
Mean	0.306	0.263	0.219	0.062	0.028	0.023
Absolute mean	1.098	1.448	1.462	1.208	1.593	1.555
Minimum	-2.600	-3.312	-3.060	-2.607	-3.127	-3.473
Maximum	3.471	3.968	4.043	4.109	4.187	3.789
Standard Deviation	1.338	1.698	1.778	1.496	1.874	1.859
Noise-signal ratio	0.631	0.801	0.839	0.706	0.884	0.877
Correlation w/Initial	**-0.685**	**-0.534**	**-0.457**	**-0.712**	**-0.575**	**-0.539**
Correlation w/Final	0.168	**0.424**	**0.546**	0.196	**0.415**	**0.448**
AR(1)	**0.844**	**0.870**	**0.840**	**0.944**	**0.964**	**0.959**

C. Output Gap Revision: Using BP Filter.

	Real ($r_{t,i}^{BP}$)			Quasi-real ($r_{t,i}^{Q,BP}$)		
Statistic / Horizon i	1Y	2Y	Final^{2018Q2}	1Y	2Y	Final^{2018Q2}
Mean	**0.874**	**0.931**	**0.738**	**0.595**	**0.743**	**0.573**
Absolute mean	0.985	1.150	1.195	0.841	1.019	1.181
Minimum	-0.802	-1.614	-2.420	-1.308	-1.426	-1.913
Maximum	3.861	3.711	3.846	3.381	3.299	3.493
Standard Deviation	0.885	1.027	1.302	0.950	1.042	1.305
Noise-signal ratio	0.505	0.586	0.743	0.543	0.595	0.746
Correlation w/Initial	-0.057	-0.007	-0.115	-0.112	-0.064	-0.201
Correlation w/Final	**0.653**	**0.760**	**0.719**	**0.656**	**0.737**	**0.646**
AR(1)	**0.848**	**0.894**	**0.930**	**0.887**	**0.927**	**0.943**

Source: Authors' elaboration.
Note: Bold values indicate statistical significance at the level of 0.05.Abbreviations: BR denotes benchmark revisions, HP denotes Hodrick-Prescott filter, BP denotes Band Pass filter.

Table C2. Results of the Estimation Exercises for Output Gap

Output Gap	Model 1 (revision variables)	Wald	R2	Adj. R2	RMSE1/ RMSE4	RMSE2/ RMSE4	RMSE3/ RMSE4
			1 Quarter revision				
$r_{t,t+1+1}$	Rev1q – Rev2y	0.145	0.278	0.094	0.639	0.723	0.717
$r_{t,t+1+1}^{HP}$	Rev1q – Rev2q	**0.000**	0.784	0.760	0.533	0.536	1.100
$r_{t,t+1+1}^{BP}$	Rev1q – Rev1½y	**0.009**	0.343	0.212	0.668	0.750	0.764
$r_{t,t+1+1}^{Q,HP}$	Rev1q – Rev1½y	**0.000**	0.793	0.752	0.805	0.885	1.599
$r_{t,t+1+1}^{Q,BP}$	Rev1q – Rev1½y	**0.000**	0.463	0.356	0.613	0.848	0.882
			1 Year revision				
$r_{t,t+1+4}$	Rev2q	0.680	0.061	-0.031	1.193	1.188	1.161
$r_{t,t+1+4}^{HP}$	Rev1q – Rev1¼y	**0.000**	0.591	0.516	1.308	1.362	1.847
$r_{t,t+1+4}^{BP}$	Rev1¾y	0.412	0.100	0.003	1.838	1.871	1.813
$r_{t,t+1+4}^{Q,HP}$	Rev2y	**0.000**	0.637	0.598	2.098	2.184	3.133
$r_{t,t+1+4}^{Q,BP}$	Rev1q – Rev1¼y	0.133	0.228	0.085	2.070	2.169	2.125
			2 Years revision				
$r_{t,t+1+8}$	Rev1q – Rev1¼y	0.385	0.179	0.015	1.283	1.319	1.335
$r_{t,t+1+8}^{HP}$	Rev1q – Rev2y	**0.000**	0.624	0.513	1.519	1.716	2.092
$r_{t,t+1+8}^{BP}$	Rev1¾y	0.052	0.207	0.115	2.082	2.262	2.180
$r_{t,t+1+8}^{Q,HP}$	Rev2y	**0.000**	0.631	0.587	2.492	2.828	3.656
$r_{t,t+1+8}^{Q,BP}$	Rev2y	**0.008**	0.280	0.195	2.412	2.570	2.566
			Final revision (2018Q2)				
$r_{t,f}$	Rev2q	**0.000**	0.556	0.511	1.246	1.260	1.781
$r_{t,f}^{BR}$	Rev1¾y	0.064	0.183	0.097	0.748	0.857	0.838
$r_{t,f}^{HP}$	Rev2y	**0.000**	0.554	0.509	1.395	1.716	1.941
$r_{t,f}^{BP}$	Rev2y	**0.019**	0.220	0.141	2.605	2.937	2.862
$r_{t,f}^{Q,HP}$	Rev2y	**0.000**	0.630	0.593	2.527	3.092	3.771
$r_{t,f}^{Q,BP}$	Rev1q – Rev2y	**0.015**	0.371	0.214	2.762	3.169	3.125

Source: Authors' elaboration.

Notes: Bold values indicate statistical significance at the level of 0.05. Model 1 includes constant, initial announcement, trend and seasonal dummies. Abbreviations: BR denotes benchmark revisions, HP denotes Hodrick-Prescott filter, BP denotes Band Pass filter.

Annex D

Table D1. Average forecasting errors. CPI excluding food and energy, non-tradable items (W=60)

Models	RMSFE				RMSE relative to Staff			
	h=1	*h*=2	*h*=4	*h*=6	*h*=1	*h*=2	*h*=4	*h*=6
AR(4)	0.76	0.98	1.28	1.28	0.96	0.93	0.90	0.90
HP RT	0.78	1.02	1.36	1.37	0.98	0.96	0.96	0.96
HP Quasi RT	0.80	1.03	1.42	1.38	1.02	0.98	1.00	0.96
BP RT	0.79	1.03	1.37	1.35	1.00	0.97	0.96	0.94
BP Quasi RT	0.81	1.06	1.38	1.34	1.03	1.00	0.97	0.94
BN RT	0.78	1.03	1.41	1.38	0.99	0.97	0.99	0.96
BN Quasi RT	0.78	1.01	1.38	1.33	0.99	0.96	0.97	0.93
LT RT	0.86	1.16	1.54	1.39	**1.08**	1.10	1.08	0.97
LT Quasi RT	0.84	1.12	1.48	1.39	1.06	1.05	1.04	0.97
QT RT	0.86	1.16	1.54	1.39	**1.08**	1.10	1.08	0.97
QT Quasi RT	0.84	1.12	1.48	1.39	1.06	1.05	1.04	0.97
Annualized Growth F	0.77	1.01	1.32	1.35	0.97	0.95	0.93	0.95
Annual Growth RT	0.77	1.05	1.44	1.38	0.98	1.00	1.01	0.97
Annual Growth F	0.79	1.04	1.38	1.35	1.00	0.98	0.97	0.94
Staff	0.79	1.06	1.43	1.43	1.00	1.00	1.00	1.00
Staff F	0.79	1.01	1.36	1.34	1.00	0.96	0.95	0.94
HP F	0.80	1.01	1.37	1.34	1.01	0.96	**0.96**	0.94
BP F	0.82	1.06	1.35	1.37	1.04	1.00	0.95	0.96
BN F	0.78	1.02	1.38	1.33	0.99	0.96	0.97	0.93
LT F	0.82	1.08	1.47	1.39	1.04	1.02	1.03	0.97
QT F	0.82	1.08	1.47	1.39	1.04	1.02	1.03	0.97
Median filters F	0.82	1.06	1.38	1.37	1.04	1.00	0.97	0.96

Note: see note to Table 6 in the main text.

Table D2. Average forecasting errors. Wage inflation (W=60)

Models	RMSFE				RMSE relative to Staff			
	h=1	*h*=2	*h*=4	*h*=6	*h*=1	*h*=2	*h*=4	*h*=6
AR(4)	0.45	0.63	1.12	1.31	1.08	1.05	1.01	0.97
HP RT	0.44	0.63	1.13	1.36	1.04	1.04	1.02	1.01
HP Quasi RT	0.44	0.61	1.15	1.39	1.04	1.01	1.04	1.03
BP RT	0.44	0.60	1.08	1.27	1.05	0.99	0.97	0.94
BP Quasi RT	0.44	0.60	1.10	1.31	1.05	0.99	0.99	0.97
BN RT	0.43	0.59	0.98	1.12	1.02	0.98	0.88	0.83
BN Quasi RT	0.43	0.57	0.95	1.10	1.02	0.94	0.86	0.82
LT RT	0.53	0.75	1.27	1.31	**1.26**	**1.25**	1.14	0.97
LT Quasi RT	0.50	0.72	1.28	1.37	**1.20**	**1.19**	**1.15**	1.02
QT RT	0.53	0.75	1.27	1.31	**1.26**	**1.25**	1.14	0.97
QT Quasi RT	0.50	0.72	1.28	1.37	**1.20**	**1.19**	**1.15**	1.02
Annualized Growth RT	0.44	0.63	1.05	1.14	1.05	1.05	0.94	0.84
Annual Growth RT	0.42	0.58	0.94	1.11	1.01	0.96	0.85	0.82
Annual Growth F	0.43	0.56	0.92	1.09	1.01	0.92	0.83	0.81
Staff	0.42	0.60	1.11	1.35	1.00	1.00	1.00	1.00
Staff F	0.42	0.58	1.08	1.32	1.01	0.96	0.97	0.98
HP F	0.44	0.61	1.16	1.41	1.05	**1.01**	1.05	1.04
BP F	0.43	0.58	1.11	1.34	1.03	0.96	1.00	0.99
BN F	0.43	0.57	0.96	1.11	1.02	0.94	0.87	0.82
LT F	0.48	0.69	1.31	1.47	**1.14**	**1.14**	1.18	**1.09**
QT F	0.48	0.69	1.31	1.47	**1.14**	**1.14**	1.18	**1.09**
Median filters F	0.44	0.61	1.16	1.41	1.05	1.01	1.05	1.04

Note: see note to Table 6 in the main text.

Table D3. Average forecasting errors. Inflation excluding food and energy (W=60)

Inflation Expectations from EEE used in equation (5)

Models	RMSFE				RMSE relative to Staff			
	***h*=1**	***h*=2**	***h*=4**	***h*=6**	***h*=1**	***h*=2**	***h*=4**	***h*=6**
AR(4)	0,63	1,12	1,86	1,72	1,01	1,06	1,04	**1,03**
HP RT	0,63	1,07	1,79	1,75	1,02	1,01	1,01	1,04
HP Quasi RT	0,65	1,09	1,84	1,72	**1,04**	1,03	1,03	1,03
BP RT	0,65	1,10	1,81	1,79	1,04	1,04	1,02	1,07
BP Quasi RT	0,66	1,11	1,82	1,77	**1,06**	1,05	1,02	1,06
BN RT	0,64	1,11	1,93	1,93	1,03	1,06	1,09	1,15
BN Quasi RT	0,66	1,16	2,00	1,90	1,06	1,10	1,12	1,14
LT RT	0,65	1,19	2,11	1,98	**1,05**	1,13	1,18	1,18
LT Quasi RT	0,67	1,22	2,10	1,92	**1,09**	1,15	1,18	1,14
QT RT	0,65	1,19	2,11	1,98	**1,05**	1,13	1,18	1,18
QT Quasi RT	0,67	1,22	2,10	1,92	**1,09**	1,15	1,18	1,14
Annualized Growth RT	0,63	1,09	1,87	1,86	1,02	1,03	1,05	**1,11**
Annual Growth RT	0,62	1,09	1,94	1,92	1,00	1,03	1,09	1,15
Annual Growth F	0,65	1,12	1,96	1,92	1,05	1,07	1,10	1,14
Staff	0,62	1,05	1,78	1,68	1,00	1,00	1,00	1,00
Staff F	0,62	1,00	1,67	1,65	**0,99**	0,95	0,94	0,99
HP F	0,62	0,99	1,68	1,61	0,99	0,94	0,94	**0,96**
BP F	0,66	1,05	1,66	1,67	1,06	0,99	**0,93**	1,00
BN F	0,66	1,15	2,00	1,90	1,06	1,10	1,12	1,14
LT F	0,66	1,17	2,04	1,88	1,06	1,11	1,14	**1,12**
QT F	0,66	1,17	2,04	1,88	1,06	1,11	1,14	**1,12**
Median filters F	0,66	1,15	2,00	1,88	1,06	1,10	1,12	1,12

Note: see note to Table 6 in the main text.

Data appendix

Real GDP rest (ex - mining, fishing and electricity, gas and water) seasonally adjusted, in logs

Source	Sample
For **real time data**, Real GDP rest refers to this time-series available at each MP report. In December 2009, the new model MAS and the incumbent MEP started to be averaged to produce baseline forecasts. One decision implemented to simplify the process was to use data starting in 2001.Q3 onwards. This sub-sample period which is known as the Inflation Targeting. For these newer MP reports data spanning from 1991 to 2001.Q2 is not available. Therefore, we filled-in the missing data using backward interpolation using q-o-q variation of the full sample available in the MP Report issued in September 2009. Evidently, observed levels of the third quarter of 2001 are those available in each MP report. More recent vintages of data on PIB rest are unavailable because this measure is phased out. More precisely, staff's analysis conducted at the CB of Chile now focus on non-mining GDP instead. See Fuentes *et al.* (2018) for documentation on this new GDP measure. Non-mining GDP data is publicly available at www.bcentral.cl. For **last available data** we denote the data used at the MP report of June 2018, with similar treatment for the period 1991 to 2001.Q2 Seasonal adjustment methods are official since 2013. For further details on the methodology, see Cobb and Jara (2013).	Full: 1991.Q1 – 2018.Q1 Revisions use Inflation targeting period: 2001.Q3 to 2018.Q1 Forecasting exercise: 1991.Q1 – 2018.Q1

Core Inflation seasonally adjusted, consumer price index 2013=100:

Source	Period
Core Inflation without food and energy, backward interpolation linked. For detailed methodology, see Sansone and Rubio (2015).	1991.Q1 onwards
Median Inflation using index price sub-categories, constructed by backward interpolation using raw data from Sansone and Rubio (2015).	2000.Q1 onwards
Core Inflation computed with a four principal components using 130 sub-categories of the CPI (7 sub-categories are disregarded due to changes in their definitions). These subcategories are calculated by backward interpolation, see Sansone and Rubio (2015).	2000.Q1 onwards

Real exchange rate (RER), index 1986=100

Source	Period
Central Bank of Chile. Methodology of calculation: https://si3.bcentral.cl/estadisticas/Principal1/Metodologias/EC/PARIDADES/Indices_tipo_cambio_precios_externos_distintas_medidas.pdf	1991.T1 onwards

One-year ahead inflation expectations:

Source	Period
Expectations assumed to be equal to one year ahead effective inflation (perfect foresight)	1991.Q1 to 2000.Q4
Survey of Market participants (EEE). Available at https://www.bcentral.cl/es/web/guest/expectativas-economicas	2001.Q1 onwards
Forecasts of inflation available at each MP report	2001.Q2 onwards (first MP Report May 2000)

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