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FORECASTING CHILEAN INFLATION WITH INTERNATIONAL FACTORS*

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Abstract

In this paper we build forecasts for Chilean year-on-year inflation using simple time-series models augmented with different measures of international inflation. Broadly speaking, we construct two families of international inflation factors. The first family is built using year-on-year inflation of 18 Latin American (LA) countries (excluding Chile). The second family is built using year-on-year inflation of 30 OECD countries (excluding Chile). We show sound in-sample and pseudo out-of-sample evidence indicating that these international factors do help forecast Chilean inflation at several horizons. Incorporating the international factors reduce the Root Mean Squared Prediction Error of pure univariate SARIMA models statistically speaking. We also show that the predictive pass-through from international to local inflation has increased in the recent years. As a final exercise we construct another international inflation factor as an average of the inflation of fifteen countries from which Chile gets a high percentage of its imports. With the aid of this factor the models outperform our univariate benchmarks but also underperform the results obtained with the broader factors built with LA or OECD countries, suggesting that imported inflation is not the only channel explaining our findings.

Resumen

En este documento construimos pronósticos para la inflación anualizada en Chile utilizando simples modelos de series de tiempo expandidos con distintas medidas de inflación internacional. En términos generales utilizamos dos familias de factores internacionales de inflación. La primera familia es construida a partir de la inflación anualizada de 18 países de Latino América (excluyendo a Chile). La segunda familia es construida a partir de la inflación anualizada de 30 países de la OECD (excluyendo a Chile). Nuestros resultados muestran una sólida evidencia indicando que estos factores internacionales ayudan a predecir la inflación chilena a diferentes horizontes en ejercicios dentro como fuera de muestra. La incorporación de los factores internacionales ayuda a reducir la Raíz del Error Cuadrático Medio de pronóstico de los modelos SARIMA univariados en forma estadísticamente significativa. También mostramos que el traspaso predictivo desde inflación internacional a local ha crecido en los últimos años. Como ejercicio final, construimos otro factor internacional como un promedio de las inflaciones de quince países desde los cuales Chile obtiene un alto porcentaje de sus importaciones. Con la ayuda de este factor los modelos predicen mejor que nuestros marcos de referencia univariados pero predicen peor que con la ayuda de los factores

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internacionales basados en países de Latino América o de la OECD, lo cual sugiere que la inflación importada no es el único canal de transmisión que puede explicar nuestros resultados

I. Introduction

In this paper we evaluate the predictive content of an international inflation factor to forecast Chilean headline inflation. Our motivation relies on two important results reported in a vast recent literature. In the first place, several papers have reported a poor performance of Phillips curve–based forecasts for the US. Atkeson and Ohanian (2001), Clark and McCracken (2006) and Stock and Watson (2008) are just a few examples of this regularity. For the case of Chile, Pincheira and Rubio (2010) have also reported a similar phenomenon suggesting that measures of domestic activity are not very good predictors for domestic inflation. In the second place, a few relatively recent articles report an important pass-through from some measures of industrialized international inflation to local inflation. In particular Ciccarelli and Mojon (2010) and West (2008) find that local inflation in OECD countries is importantly driven by a common inflation factor. Other interesting papers on this topic are Mumtaz and Surico (2006) and Neely and Rapach (2011).

The disconnection between activity measures and inflation has been remarkably strong in Chile during the last years. For instance, for the period March 2010–October 2013, the average quarterly GDP growth rate in Chile was 5.5% whereas the inflation rate during the same period was only 2.6%, below the target of 3% and below the average of 3.2% since 2000, when Chile was in the early stages of a stationary inflation targeting regime. In summary, in the last years the Chilean economy grew rapidly with no inflation. Out of the many possible reasons that might explain this situation, we place our attention on the relationship between Chilean domestic inflation and international inflation. We focus on the predictive side of the question, so we are not looking for the specific transmission channels between international and domestic inflation. Instead, the objective of this paper is to evaluate if international inflation has predictive information for Chilean domestic inflation, beyond that contained in good univariate benchmarks. Therefore, we leave more fundamental questions about possible transmission channels for further research. Our contribution to the relevant literature is mostly empirical, as to our knowledge, there are no papers addressing this question for an emerging small open economy like Chile. Previous works like those of Ciccarelli and Mojon (2010) and West (2008) analyze only a set of OECD countries for a sample period in which Chile was not a member of this selected group of economies[2].

With this in mind, we construct two families of international inflation factors. The first family is built using year-on-year inflation of 18 Latin American countries (excluding Chile). The second family is built using year-on-year inflation of 30 OECD countries (excluding Chile). We find sound

[2] West (2008) is a presentation based on the article by Engel, Mark and West (2012).

in-sample and pseudo out-of-sample evidence indicating that these international factors do help forecast Chilean inflation at several horizons. Incorporating the international factors reduce the Root Mean Squared Prediction Error (RMSPE) of pure univariate models statistically speaking. We also show that the predictive pass-through from international to local inflation has increased in the recent years. Interestingly, the behavior of OECD versus LA factors is heterogeneous. Nevertheless, the overall minima for forecasting horizons of 1, 3, 6 and 12 months are obtained using the simple average of the OECD countries as an international factor. When forecasting at 24 months ahead a modest edge in favor of a model using a LA based factor is detected.

As a final exercise we construct another international inflation factor as an average of the inflation of fifteen countries from which Chile gets a high percentage of its imports. With the aid of this factor the models outperform our univariate benchmarks but underperform the results obtained with the broader factors built with LA or OECD countries, suggesting that imported inflation is not the only channel explaining our findings.

The rest of the paper is organized as follows. Section II develops the econometric framework that we use in the paper, describes our data and shows the construction of the international inflation factors. Section III shows in-sample and pseudo out-of-sample results. Finally, Section IV concludes.

II. Data and Econometric Setup

1. Our Data

For our main analysis we consider the Consumer Price Index (CPI) of a total of 49 countries at a monthly frequency. The data cover the sample period from January 1994 to March 2013. Our set of countries includes Chile plus 30 OECD economies (displayed in Table 1) and 18 Latin American (LA) countries, which are listed in Table 2. We obtain the CPI for Chile directly from the National Statistics Institute, which is the government agency in charge of the construction of the CPI. For the rest of the 30 OECD countries we obtained CPI series from the Main Economic Indicators section of the OECD web page. For the 18 LA economies we use either their central banks or the corresponding national statistics institutes as source for the data.

As our main objective is to predict Chilean inflation using an international inflation factor, we consider two options for the construction of such a factor. The first one follows Ciccarelli and Mojon (2010) to build an OECD-based factor. The second option considers only Latin American countries, which are similar in culture and some particular aspects to the Chilean Economy (similarities include dependence in commodities, language, trade agreements, etc). It is important to mention that for the construction of our factors we rule out some countries from the total OECD and Latin American countries for data availability[3].

Table 1
Sample of OECD Countries (excluding Chile)

Austria	Iceland	Poland
Belgium	Ireland	Portugal
Canada	Israel	Slovak Republic
Czech Republic	Italy	Slovenia
Denmark	Japan	Spain
Finland	Korea, Rep.	Sweden
France	Luxembourg	Switzerland
Germany	Mexico	Turkey
Greece	Netherlands	United Kingdom
Hungary	Norway	United States

Source: Author´s elaboration

Table 2
Sample of Latin American Countries (excluding Chile)

Argentina	Honduras
Bolivia	México
Brazil	Nicaragua
Columbia	Panamá
Costa Rica	Paraguay
Ecuador	Peru
El Salvador	Dominican Republic
Guatemala	Uruguay
Haiti	Venezuela

Source: Author´s elaboration

Our basic unit of analysis corresponds to year-on–year (y-o-y) inflation rate computed according to the following simple expression:

[3] In our sample of OECD economies we rule out the cases of New Zealand and Australia due to the unavailability of CPI information at a monthly frequency. We also rule out the case of Estonia due to data availability. In Estonia we only find data for the year 1998 onward. To reduce distortions coming from considerations of different sample periods, we just work with the list of 30 OECD economies with information at a monthly frequency during the entire sample period January 1994- March 2013. Finally, from the group of LA countries we remove Cuba because we were not able to find official CPI data at a monthly frequency.

$$\pi_t = 100[\mathrm{Ln}(\mathrm{CPI}_t) - \mathrm{Ln}(\mathrm{CPI}_{t-12})]$$

We depart from Stock and Watson (2002) and Ciccarelli and Mojon (2010) in that we focus only on forecasting year-on-year inflation rate at different horizons. We also depart from those articles in the construction of multistep ahead forecasts. We do not consider the direct forecasting strategy used in those articles and rely instead on a dynamic or iterated forecasting set up for the construction of forecasts at long horizons.

With the year-on-year transformation we end up with a total of 219 observations from January 1995 to March 2013. Tables 1-2 in the appendix display descriptive statistics of the different inflation series.

2. The International Inflation Factor

We construct three different international inflation factors for each group of economies (OECD and LA). We first consider the simple average of the year-on-year inflation rates of the economies under consideration:

$$f_t = \frac{1}{N}\sum_{i=1}^{N} \pi_{i,t}$$

where N=30 when working with the sample of OECD countries and N=18 when working with Latin American Countries. $\pi_{i,t}$ represents the year-on-year inflation rate of country i at time t.

Our second international factor is constructed as the weighted average of the first two principal components of the set of year-on-year inflation rates for each group of economies (OECD and LA excluding Chile).

$$f_t = \sum_{i=1}^{2} w_i . pc_{i,t}$$

In this case, the weights w_i are constructed as the share of the corresponding eigenvalue over the sum of the two relevante eigenvalues

$$w_i = \frac{\lambda_i}{\sum_{j=1}^{2} \lambda_j}$$

Finally, our third international factor is constructed as the weighted average of the first two components coming from the Partial Least Squares (PLS) sequential procedure. Differing from the traditional principal components analysis, our PLS components take into consideration both the set of possible predictors (y-o-y inflation of OECD or LA countries at time t, excluding Chile) and also the variable we are trying to predict, which in this case correspond to Chilean y-o-y inflation at time t+1. Instead of picking the components that maximize the share of variance of the explanatory variables, now we pick components maximizing the covariance between our dependent variable and different normalized linear combinations of the set of predictors. Once the first component is obtained, it is possible to regress the dependent variable over a constant and this factor, and also it is possible to regress all the predictors over a constant and the first factor. The residuals from these regressions will form a new dependent variable and a new set of predictors, so the method is repeated over these residual variables. More details about how the PLS methodology can be implemented are found in Poncela, Rodrígues and Sánchez-Mangas (2009), Maitra and Yan (2008) and Abdi (2003).

We judgmentally consider only two latent components for the PLS approach. With these two components we build the following weighted average factor f_t :

$$f_t = \sum_{i=1}^{2} l_i . w_{i,t}$$

where l_i represents each one of the two latent factors, and $w_{i,t}$ represents the weights associated to those factors which are proportional to the share of variance of the set of international inflations that these latent factors are able to explain.

Figures 1-2 in the appendix show the evolution of Chilean inflation and our three international factors: Simple Average (SA), Principal Components Analysis (PCA) and Partial Least Squares (PLS). Figure 1 shows results when the factors are computed with OECD data. Figure 2 depicts the factors computed with Latin American inflations. On the one hand it is remarkable how similar all three international factors look like. On the other hand is quite obvious that factors built with Latin American countries display an upward bias. This is not much of a concern for our analysis, as we work with the first difference of the international factors as will be clear in subsequent sections. All in all it is very impressive how our international factors seem to comove with Chilean inflation.

3. Forecast Evaluation Framework

We evaluate the predictive ability of our benchmark models against their augmented versions with the international factor both in-sample and out-of-sample. To describe the out-of-sample exercise, let us assume that we have a total of T+1 observations of π_t for Chile. We generate a sequence of P(h) h-step-ahead forecasts estimating the models in rolling windows of fixed size R. For instance, to generate the first h-step-ahead forecasts, we estimate our models with the first R observations of our sample. Then, these forecasts are built with information available only at time R and are compared to the realization π_{R+h}. Next, we estimate our models with the second rolling window of size R that includes observations through R+1. These h-step-ahead forecasts are compared with the realization π_{R+h+1}. We iterate until the last forecasts are built using the last R available observations for estimation. These forecasts are compared with the realization π_{T+1}. We generate a total of P(h) forecasts, with P(h) satisfying R+(P(h)-1)+h=T+1. So

$$P(h)=T+2-h-R$$

Forecast accuracy is measured in terms of RMSPE. Because this is a population moment, we estimate it using the following sample analog:

$$\mathrm{SRMSPE} = \sqrt{\frac{1}{P(h)} \sum_{t=R}^{T+1-h} \left(\pi_{t+h} - \hat{\pi}_{t+h|t}\right)^2}$$

where SRMSPE stands for “Sample Root Mean Squared Prediction Error” and $\hat{\pi}_{t+h|t}$ represents the forecast of π_{t+h} made with information known up until time t.

We carry out inference about predictive ability by considering pairwise comparisons between each univariate model and its augmented version.

Inference is carried out within the frameworks developed by Giacomini and White (2006) (henceforth GW) and Clark and West (2007) (henceforth CW). We first focus on the unconditional version of the t-type statistic proposed by GW. This test has the distinctive feature of allowing comparisons between two competing forecast methods instead of two competing models. This is desirable for our purpose, which is mainly focused on the forecasts that different models estimated with rolling windows of fixed size, can provide.

According to the unconditional version of the Giacomini and White (2006) test, we focus on testing the following null hypothesis

$$H_0\colon \mathrm{E}\left(\hat{d}_t(h)\right) \leq 0$$

against the alternative:

$$\mathbf{H_A = E(\hat{d}_t(h)) > 0}$$

where

$$\hat{d}_t(h) = \left(\pi_{t+h} - \hat{\pi}_{1,t+h|t}\right)^2 - \left(\pi_{t+h} - \hat{\pi}_{2,t+h|t}\right)^2$$

and $\hat{\pi}_{1,t+h|t}$ and $\hat{\pi}_{2,t+h|t}$ denote the h-step ahead forecasts generated from the two models under consideration. Model 1 is the parsimonious or "small" model that is nested in the larger model 2. In other words, model 2 would become model 1 if some of its parameters would be set to zero.

We focus on one sided tests because we are interested in detecting forecast superiority. Our null hypothesis poses that forecasts generated from the nested model perform at least as well as forecasts generated from the larger model. Our alternative hypothesis claims superiority of the forecasts generated by the larger model.

Second, we focus on the Clark and West (2007) statistic, which is mainly aimed at evaluating models in an out-of-sample fashion. With the CW test we evaluate whether the international factor provides additional information to that already contained in our univariate benchmarks.

The CW test can be considered either as an encompassing test or as an adjusted comparison of Mean Squared Prediction Errors (MSPE). The adjustment is made in order to make a fair comparison between nested models. Intuitively, this test removes a term that introduces noise when a parameter, that should be zero under the null hypothesis of equal MSPE, is estimated.

The core statistic of the Clark and West (2007) test is constructed as follows

$$\hat{z}_{t+h} = \left(\hat{e}_{1,t+h}\right)^2 - \left[\left(\hat{e}_{2,t+h}\right)^2 - \left(\hat{\pi}_{1,t+h|t} - \hat{\pi}_{2,t+h|t}\right)^2\right]$$

where $\hat{e}_{1,t+h} = \pi_{t+h} - \hat{\pi}_{1,t+h|t}$ and $\hat{e}_{2,t+h} = \pi_{t+h} - \hat{\pi}_{2,t+h|t}$ represent the corresponding forecast errors.

With some little algebra it is straightforward to show that $\hat{z}_{t+h}$ could also be expressed as follows

$$\mathrm{SMSPE-Adjusted} = \frac{2}{P(h)} \sum_{t=R}^{T+1-h} \hat{e}_{1,t+h}\left(\hat{e}_{1,t+h} - \hat{e}_{2,t+h}\right) \quad (1)$$

This statistic is used to test the following null hypothesis

$$H_0: E(\mathrm{SMSPE-Adjusted}) = 0$$

against the alternative

$$H_A: E(\mathrm{SMSPE-Adjusted}) > 0$$

Clark and West (2007) suggest a one sided test for a t-type statistic based upon the core statistic in (1). They recommend asymptotically normal critical values for their test.

It is important to emphasize here that both tests, GW and CW, are different in a number of aspects. One of the most important differences, however, is that they are designed for different purposes. While the GW 2006 test is comparing the ability of two different forecasting methods, the CW 2007 test is testing for model adequacy. In other words, it is testing whether the larger model is more appropriate than the smaller model. Consequently, we expect these two tests to deliver different results. Most likely, the Clark and West test will be able to show more rejections of the null hypothesis than the GW test. We will see this when describing our empirical results[4].

4. Forecasting Models

Differing from Ciccarelli and Mojon (2010) and Stock and Watson (2002) we rely on a different set of univariate time-series models to produce benchmark inflation forecasts. Pincheira and García (2012) and Pincheira and Medel (2012b) show that an extended family of SARIMA models produce competitive out-of-sample forecasts at short and long horizons when compared to traditional univariate benchmarks used in the literature. This is shown for Chile, but also for a number of different countries experiencing either stable or unstable inflation.

We focus on the additional ability that the international inflation factor may have over our univariate strategies to predict inflation in Chile. We consider 10 different univariate specifications following Pincheira and Medel (2012b). Then, we compare each of these univariate specifications

[4] In Pincheira (2013) there is some discussion about the linkage between the Clark and West (2007) test and reductions in MSPE for the particular case in which the null hypothesis is a martingale difference model.

with their augmented versions. We denote each of the benchmarks as SARIMA[j], j=1,2,…,10. The augmented versions of these models are denoted FASARIMA[j], j=1,2,…,10, where FASARIMA stands for Factor Augmented SARIMA. Table 3 summarizes the FASARIMA specifications under consideration.

Table 3
FASARIMA MODELS

FS [1] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1}$
FS [2] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \varepsilon_t - \theta_E\varepsilon_{t-12}$
FS [3] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12}$
FS [4] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\varepsilon_{t-13}$
FS [5] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \phi(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\varepsilon_{t-13}$
FS [6] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \phi(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12}$
FS [7] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \phi(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta_E\varepsilon_{t-12}$
FS [8] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \phi(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1}$
FS [9] : $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \phi(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t$
FS [10]: $\pi_t - \pi_{t-1} = \gamma(f_{t-1} - f_{t-2}) + \varepsilon_t$

Source: Authors' elaboration.

In Table 3 π_t represents Chilean year-on-year inflation rate, ε_t represents a white noise process and f_t represents the international inflation factor. It is worth noticing that the univariate SARIMA benchmarks are also implicitly contained in Table 3. As a matter of fact, setting $\gamma = 0$ in all the models in Table 3 allows us to recover the 10 univariate SARIMA models used as benchmarks. Interestingly, more than half of the models in Table 3 contain explicit moving average seasonal terms. This might seem counterintuitive as we are trying to predict year-on-year Chilean inflation rates. Ciccarelli and Mojon (2010), for instance, claim that year-on-year transformations have no seasonal patterns. Nevertheless, it is relatively simple to show that the year-on-year transformation only removes additive seasonal terms of a very particular kind. More complex forms of seasonality will survive to this transformation of the data. This is probably one of the reasons why the benchmarks implicitly contained in Table 3 fare well with respect to usual competitors. See Pincheira and Medel (2012b) for details.

To create multi-step ahead forecasts we use the iterated method relying on the following ARIMA specification for the international factor:

$$f_t - f_{t-1} = \alpha(f_{t-1} - f_{t-2}) + u_t - \varphi_E u_{t-12} \quad (2)$$

where u_t is a white noise process. We notice that in all our equations we have imposed a unit root to generate Chilean inflation forecasts and the international inflation factor forecasts. This is also in line with important papers in the forecasting literature, see Stock and Watson (2012) and Atkeson and Ohanian (2001) for instance. Besides, Pincheira and Medel (2012a) provide interesting insights regarding the use of unit root-based forecasts when forecasting stationary variables. We notice also that all the specifications under consideration are driftless expressions. That is done on purpose to avoid the presence of deterministic trends in long-run forecasts[5].

It is worth noticing that most of the traditional unit root tests show mixed results when analyzing our different international factors. In contrast, they are consistent with the null hypothesis of a unit – root for Chilean year-on-year inflation.

Table 4
Chilean Inflation: Unit Root Testing
(Full Sample: 1995:01 – 2013:03)

	ADF	DF GLS	PP	KPSS
π_t	-2.532	-1.828	-2.843	0.165**
$\pi_t - \pi_{t-1}$	-6.324***	-5.732***	-9.789***	0.037

Note: * p<10%, ** p<5%, *** p<1%. ADF test (Augmented Dickey – Fuller), DF-GLS test (Elliot, Rothenberg and Stock (ERS)) and PP test (Phillips-Perron) test the null hypothesis of a unit root. KPSS tests (Kwiatkowski, Phillips, Schmidt y Shin) the null hypothesis of stationarity.

Source: Authors' elaboration.

Table 5
International Inflation Factor LA (18): Unit Root Testing
(Full Sample: 1995:01 – 2013:03)

	f_t				$f_t - f_{t-1}$			
LATAM (18)	**ADF**	**DF GLS**	**PP**	**KPSS**	**ADF**	**DF GLS**	**PP**	**KPSS**
SA	-4.36***	-1.32	-4.94***	0.22***	-6.05***	-3.64***	-5.84***	0.10
PCA	-2.93	-1.87	-2.72	0.23***	-8.00***	-7.33***	-8.24***	0.04
PLS	-2.45	-2.20	-2.75	0.21**	-7.58***	-7.70***	-8.34***	0.04

Note: * p<10%, ** p<5%, *** p<1%. ADF test (Augmented Dickey – Fuller), DF-GLS test (Elliot, Rothenberg and Stock (ERS)) and PP test (Phillips-Perron) test the null hypothesis of a unit root. KPSS tests (Kwiatkowski, Phillips, Schmidt y Shin) the null hypothesis of stationarity.

Source: Authors' elaboration.

[5] See Pincheira and Medel (2012a) for further details.

Table 6
International Inflation Factor OECD (30): Unit Root Tests
(Full Sample: 1995:01 – 2013:03)

	f_t				$f_t - f_{t-1}$			
OECD (30)	**ADF**	**DF GLS**	**PP**	**KPSS**	**ADF**	**DF GLS**	**PP**	**KPSS**
SA	-1.95	-0.96	-2.60	0.31***	-7.51***	-2.23	-10.06***	0.03
PCA	-2.81	-1.61	-3.23*	0.13*	-7.41***	-4.45***	-9.55***	0.03
PLS	-2.89	-2.22	-3.30*	0.04	-7.16***	-5.93***	-9.92***	0.03

Note: * p<10%, ** p<5%, *** p<1%. ADF test (Augmented Dickey – Fuller), DF-GLS test (Elliot, Rothenberg and Stock (ERS)) and PP test (Phillips-Perron) test the null hypothesis of a unit root. KPSS tests (Kwiatkowski, Phillips, Schmidt y Shin) the null hypothesis of stationarity.

Source: Authors' elaboration.

Irrespective of the unit root test results, we use expressions (1) and (2) to generate our forecasts because of the vast evidence indicating that unit-root based forecasts usually work well when predicting unit-root processes or close-to-unit-root processes. See, for instance, Clements and Hendry (2001) and Pincheira and Medel (2012a) and the references therein stated.

IV. Empirical Results

1. In Sample Analysis

The next table 7 shows the estimated value of the gamma parameter for all the FASARIMA models described in Table 3.

Table 7
Chile: Gamma Estimated In-Sample (1995:01 – 2013:03)

		FS [1]	FS [2]	FS [3]	FS [4]	FS [5]	FS [6]	FS [7]	FS [8]	FS [9]	FS [10]
LATAM	γ (SA)	0.378	0.530	0.427	0.498	0.435	0.357	0.374	0.432	0.280	0.389
	t-stat.	[3.334]	[6.339]	[4.290]	[6.356]	[4.712]	[4.961]	[4.749]	[4.082]	[2.669]	[2.901]
	γ (PCA)	0.980	1.320	1.299	1.169	0.712	0.851	0.903	1.012	0.846	1.177
	t-stad.	[3.653]	[6.005]	[5.869]	[5.175]	[3.427]	[4.495]	[4.360]	[3.603]	[3.535]	[3.835]
	γ (PLS)	0.874	1.297	1.255	1.130	0.705	0.860	0.904	0.883	0.783	1.075
	t-stat.	[3.682]	[6.011]	[5.628]	[5.064]	[3.767]	[4.694]	[4.581]	[3.581]	[3.730]	[3.998]
OECD	γ (SA)	0.726	0.841	0.823	0.706	0.470	0.589	0.552	0.663	0.708	0.961
	t-stat.	[3.596]	[6.425]	[6.294]	[5.482]	[3.424]	[5.247]	[4.256]	[3.512]	[3.653]	[4.536]
	γ (PCA)	0.796	0.931	0.934	0.723	0.527	0.652	0.613	0.611	0.763	0.953
	t-stat.	[5.945]	[8.201]	[8.308]	[5.947]	[4.809]	[5.833]	[5.006]	[5.515]	[6.053]	[7.227]
	γ (PLS)	0.714	0.746	0.746	0.508	0.444	0.587	0.469	0.552	0.688	0.853
	t-stat.	[5.995]	[5.904]	[6.365]	[4.095]	[4.717]	[5.076]	[3.773]	[6.107]	[6.144]	[7.413]

Notes: The table presents the estimated coefficients and t-statistics of the gamma parameter for all FASARIMA specifications according to Table 3. The sample period is (1995:01 – 2013:03). The dependent variable is: $\pi_t - \pi_{t-1}$, and the extra predictor variable is: $f_{t-1} - f_{t-2}$. The t-statistics are constructed using HAC standard errors according to Newey and West (1987).
Source: Authors' elaboration

Table 7 also displays the corresponding t-statistics for the gamma coefficient. They are calculated using the Newey- West (1987) HAC estimator. We present results for gamma and their t-statistics for our three measures of international inflation: Simple Average (SA), Principal Components (PCA) and Partial Least Squares (PLS). Figures in Table 7 are quite impressive as for all our three measures of international inflation and in all of the specifications reported in Table 3, the gamma coefficient is positive and statistically significant at very high confidence levels. This is also robust to the construction of the international factor using either the LA or the OECD set of countries. The size of this coefficient is also remarkable. While it shows some heterogeneity, on average takes a value of 0.71, indicating that the predictive marginal pass-through from international to national inflation is far from negligible.

Table 8 provides interesting results as well. This table shows the percentage of rolling windows of s 50 and 80 observations in which the coefficient associated with the international inflation factor is significant at least at a 10% level. This significance is determined with HAC standard errors according to Newey and West (1987) starting with a first estimation window for the period 1995:01 - 2001:08 (1997:07 - 2001:08) for a window of 80 (50) observations and using the periods 2006:07 - 2013:02 (2009:01 - 2013:02) for the last window. Figures in brackets represent the average Akaike Information Criterion (AIC) across the different estimation windows.

Two salient features are worth noticing. First, we detect some instability in the significance of the international factor computed by PLS and PCA across different rolling windows. Nevertheless, much more robust results are obtained when the international factor is computed by a Simple Average in rolling windows of 80 observations. In these cases the percentage of significant coefficients ranges from 87.1% to 100% when the average is computed over LA countries, and varies from 53.6%-95% when the average is calculated over OECD countries. Second, Akaike values are always higher in the univariate specifications than in the augmented specifications, indicating a better in-sample fit of the models with the international factor.

Finally, Figure 3 in the appendix depicts the evolution of the estimates for gamma in different rolling windows for all our ten specifications. We see that these estimates are always positive and seem to be relatively stable with one important exception. Around the year 2008, all charts show a boost in the estimates from a value around 0.4 to a value around or above unity. This is an interesting pattern that might be associated to several economic reasons like the commodity boom of 2007, the Lehman crisis in September 2008 or Chile´s new methodology to construct the CPI, going from a local level to a national level. Clearly, this topic deserves further analysis in future research.

Table 8
Percentage of Rolling Windows in which the Parameter Associated to the International Inflation Factor is Significant at the 10% level [Mean of AIC]

R=50	**Average**		**PCA**		**PLS**		**SARIMAS**	
	LATAM(18)	**OECD(30)**	**LATAM(18)**	**OECD(30)**	**LATAM(18)**	**OECD(30)**		**Mean AIC**
FS [1]	79.1 [1.02]	42.4 [1.12]	51.1 [1.12]	52.5 [1.11]	66.9 [1.07]	57.6 [1.11]	**S [1]**	[1.16]
FS [2]	94.2 [0.60]	79.9 [0.63]	50.4 [0.71]	79.9 [0.62]	67.6 [0.62]	77.7 [0.64]	**S [2]**	[0.89]
FS [3]	92.8 [0.67]	76.3 [0.71]	48.9 [0.78]	69.1 [0.71]	69.8 [0.71]	72.7 [0.71]	**S [3]**	[0.90]
FS [4]	71.9 [0.50]	56.1 [0.57]	48.2 [0.57]	56.1 [0.56]	60.4 [0.54]	50.4 [0.57]	**S [4]**	[0.62]
FS [5]	70.5 [0.56]	50.4 [0.62]	46.8 [0.63]	51.1 [0.62]	64.7 [0.59]	49.6 [0.63]	**S [5]**	[0.70]
FS [6]	84.9 [0.71]	60.4 [0.71]	47.5 [0.79]	54.0 [0.70]	58.3 [0.72]	50.4 [0.70]	**S [6]**	[0.80]
FS [7]	71.9 [0.56]	56.8 [0.59]	47.5 [0.65]	57.6 [0.58]	54.0 [0.60]	50.4 [0.58]	**S [7]**	[0.69]
FS [8]	74.1 [1.02]	48.2 [1.07]	52.5 [1.11]	54.7 [1.08]	66.2 [1.05]	58.3 [1.07]	**S [8]**	[1.17]
FS [9]	82.7 [1.08]	62.6 [1.15]	52.5 [1.19]	54.0 [1.12]	68.3 [1.13]	60.4 [1.11]	**S [9]**	[1.24]
FS [10]	100.0 [1.08]	81.3 [1.17]	55.4 [1.22]	79.9 [1.14]	79.1 [1.14]	77.0 [1.13]		
Mean FASARIMAS	**82.2 [0.78]**	**61.4 [0.83]**	**50.1 [0.88]**	**60.9 [0.82]**	**65.5 [0.82]**	**60.5 [0.83]**	**Mean SARIMAS**	**[0.91]**

R=80	**Average**		**PCA**		**PLS**		**SARIMAS**	
	LATAM(18)	**OECD(30)**	**LATAM(18)**	**OECD(30)**	**LATAM(18)**	**OECD(30)**		**Mean AIC**
FS [1]	95.7 [1.00]	78.4 [1.07]	45.3 [1.09]	71.2 [1.06]	48.2 [1.04]	67.6 [1.06]	**S [1]**	[1.11]
FS [2]	100.0 [0.56]	95.0 [0.61]	65.5 [0.65]	69.1 [0.64]	70.5 [0.56]	74.8 [0.63]	**S [2]**	[0.83]
FS [3]	100.0 [0.58]	95.0 [0.64]	61.9 [0.68]	66.9 [0.66]	66.2 [0.60]	71.9 [0.65]	**S [3]**	[0.81]
FS [4]	96.4 [0.45]	59.0 [0.52]	60.4 [0.52]	39.6 [0.54]	60.4 [0.47]	43.2 [0.54]	**S [4]**	[0.58]
FS [5]	96.4 [0.48]	57.6 [0.53]	53.2 [0.56]	38.1 [0.57]	60.4 [0.49]	46.8 [0.55]	**S [5]**	[0.61]
FS [6]	97.1 [0.58]	64.0 [0.60]	59.7 [0.64]	45.3 [0.61]	62.6 [0.58]	51.1 [0.60]	**S [6]**	[0.67]
FS [7]	87.1 [0.50]	57.6 [0.53]	59.7 [0.56]	44.6 [0.54]	63.3 [0.51]	52.5 [0.53]	**S [7]**	[0.61]
FS [8]	99.3 [0.99]	53.2 [1.06]	43.9 [1.08]	60.4 [1.06]	56.8 [1.02]	68.3 [1.04]	**S [8]**	[1.10]
FS [9]	95.0 [1.04]	83.5 [1.09]	42.4 [1.15]	88.5 [1.07]	53.2 [1.08]	79.1 [1.07]	**S [9]**	[1.16]
FS [10]	95.0 [1.05]	91.4 [1.11]	51.1 [1.19]	97.8 [1.09]	54.7 [1.10]	93.5 [1.09]		
Mean FASARIMAS	**96.2 [0.72]**	**73.5 [0.78]**	**54.3 [0.81]**	**62.2 [0.78]**	**59.6 [0.75]**	**64.9 [0.78]**	**Mean SARIMAS**	**[0.83]**

Note: This table shows the percentage of rolling windows of size 50 and 80 in which the coefficient associated with the international inflation factor is significant at least at 10% level. This significance is determined with HAC standard errors according to Newey and West (1987) starting with a first estimation window for the period 1995:01 - 2001:08 (1997:07 - 2001:08) for a window of 80 (50) observations and using the periods 2006:07 - 2013:02 (2009:01 - 2013:02) for the last windows. Figures in brackets represent the average Akaike Information Criterion (AIC) across the different estimation windows. Intuitively, the lower (higher) the value of the AIC average indicates that the models have a better (worse) in-sample fit.

Source: Authors' elaboration

2. Out-of-Sample Analysis

Tables 9-10 display the ratio of RMSPE between our models estimated in rolling windows of 80 and 50 observations. Table 9 focuses on our univariate SARIMA benchmarks whereas Table 10 displays results for the same models but augmented with different versions of international factors. For the great majority of cases the use of rolling windows of 80 observations provides higher accuracy as most of the figures in Tables 9-10 are below 1.

Table 9: Ratio of RMSPE between SARIMA models estimated with Rolling Windows of 80 and 50 observations

	h=1	h=3	h=6	h=12	h=24
S [1]	0.988	0.996	0.999	0.999	0.998
S [2]	1.014	1.023	1.006	0.953	0.914
S [3]	0.962	0.979	0.975	0.952	0.892
S [4]	0.887	0.991	0.999	0.923	0.910
S [5]	0.906	0.984	0.977	0.910	0.909
S [6]	0.948	0.963	0.946	0.946	0.897
S [7]	0.995	0.999	0.990	0.970	0.923
S [8]	0.976	0.988	0.948	0.941	0.917
S [9]	1.000	1.006	1.003	0.998	0.985
S [10]	1.000	1.000	1.000	1.000	1.000

Notes: Figures less than 1 favors the estimation with 80 observations.

Source: Authors' elaboration

Due to this better predictive performance of the rolling windows with 80 observations and also for the sake of brevity, is that we report only out-of-sample results for this latter case. Tables with rolling windows of only 50 observations are available upon request.

Table 10
Ratio of RMSPE between FASARIMA models estimated with Rolling Windows of 80 and 50 observations

	LA(18) Factor					OECD(30) Factor				
	h=1	h=3	h=6	h=12	h=24	h=1	h=3	h=6	h=12	h=24
Mean FASARIMAS	**0.947**	**0.964**	**0.969**	**0.941**	**0.955**	**0.974**	**0.980**	**0.977**	**0.942**	**0.941**
Mean FS (A)	0.975	0.974	0.968	0.921	0.920	0.964	0.963	0.954	0.901	0.901
Mean FS (PCA)	0.959	0.954	0.946	0.884	0.947	0.980	0.971	0.955	0.912	0.938
Mean FS (PLS)	0.963	0.975	0.985	1.008	1.018	0.970	0.982	0.988	0.983	0.961
Mean SARIMAS	**0.969**	**0.992**	**0.984**	**0.961**	**0.938**	**0.969**	**0.992**	**0.984**	**0.961**	**0.938**
SIMPLE AVERAGE (SA)										
FS [1]	0.982	0.973	0.976	0.948	0.956	0.996	0.993	0.991	0.955	0.963
FS [2]	1.021	1.029	0.991	0.894	0.903	1.003	0.954	0.904	0.828	0.844
FS [3]	0.954	0.962	0.962	0.895	0.879	0.931	0.943	0.948	0.889	0.884
FS [4]	0.956	0.969	0.959	0.910	0.911	0.956	0.951	0.936	0.880	0.874
FS [5]	0.949	0.958	0.938	0.894	0.905	0.905	0.948	0.950	0.860	0.873
FS [6]	0.923	0.934	0.932	0.870	0.855	0.881	0.899	0.928	0.862	0.854
FS [7]	0.970	0.978	0.989	0.963	0.918	0.964	0.947	0.927	0.889	0.865
FS [8]	0.991	0.987	0.990	0.958	0.956	0.987	1.017	1.002	0.962	0.953
FS [9]	0.991	0.969	0.965	0.932	0.940	0.996	0.985	0.976	0.938	0.935
FS [10]	1.002	0.982	0.974	0.944	0.959	0.998	0.975	0.962	0.929	0.935
PRINCIPAL COMPONENTS ANALYSIS (PCA)										
FS [1]	1.000	1.018	1.008	0.925	0.958	1.002	0.984	0.970	0.956	1.001
FS [2]	0.953	0.935	0.909	0.882	0.937	1.008	0.972	0.932	0.863	0.885
FS [3]	0.949	0.936	0.947	0.876	0.911	0.947	0.953	0.953	0.898	0.927
FS [4]	0.924	0.910	0.917	0.854	0.932	0.984	0.977	0.951	0.881	0.876
FS [5]	0.882	0.899	0.896	0.828	0.911	0.941	0.971	0.947	0.889	0.881
FS [6]	0.948	0.907	0.881	0.808	0.870	0.917	0.929	0.937	0.892	0.912
FS [7]	0.941	0.898	0.909	0.853	1.010	0.981	0.977	0.962	0.915	0.896
FS [8]	1.004	1.030	1.016	0.935	0.967	1.016	1.002	0.986	0.961	0.994
FS [9]	0.998	0.989	0.980	0.916	0.985	0.995	0.973	0.954	0.928	0.982
FS [10]	0.984	0.991	0.980	0.931	0.973	1.000	0.972	0.949	0.924	0.989
PARTIAL LEAST SQUARES (PLS)										
FS [1]	0.983	0.978	0.990	1.013	1.057	0.981	0.998	1.011	1.012	1.007
FS [2]	0.981	1.022	1.029	1.009	0.981	0.995	0.992	0.995	0.973	0.945
FS [3]	0.938	0.948	0.949	0.998	1.013	0.964	0.970	0.980	0.965	0.934
FS [4]	0.961	0.987	0.994	1.009	0.960	0.956	0.973	0.977	0.958	0.902
FS [5]	0.951	0.972	0.977	0.982	0.951	0.952	0.971	0.962	0.944	0.928
FS [6]	0.903	0.942	0.939	0.958	0.948	0.907	0.960	0.970	0.963	0.925
FS [7]	0.962	1.001	0.999	1.013	0.965	0.964	0.978	0.986	0.994	0.939
FS [8]	0.975	0.976	1.000	1.028	1.063	0.983	0.998	1.005	1.008	1.008
FS [9]	0.985	0.968	0.981	1.031	1.100	0.989	0.990	0.996	1.002	0.992
FS [10]	0.978	0.966	0.986	1.033	1.108	0.996	0.995	0.998	1.005	0.999

Notes: Figures less than 1 favors the estimation with 80 observations.

Source: Authors' elaboration

i. Granger causality

Our in-sample analysis clearly indicates that the international factors do help to predict Chilean inflation. In-sample analyses, however, are usually criticized because they are relatively different from a real time forecasting exercise and also because they have shown a tendency to overfit the data. To mitigate these shortcomings, several out-of-sample tests of Granger causality have been proposed in the literature in the recent years. Table 11 shows the results of one of such tests due to Clark and West (2007). Table 11 is a summary of Table 5 in the appendix. Both tables (11 and a appendix 5) show the Clark and West (2007) t-statistic and the t-statistic of the Giacomini and White (2006) test. Shaded cells indicate statistical significance at the 10% significance value. For instance, Table 11 displays three figures in the upper left corner. All these figures are computed with one-step ahead forecast errors (h=1) coming from the FASARIMA 1 model (FS1). The first figure, 0.442, represents the core statistic of the Clark and West (2007) test. The second figure, [3.607], represents the approximately normal t-statistic of the Clark and West (2007) test. Finally, the third figure, [2.560], represents the asymptotically normal t-statistic of the Giacomini and White (2006) test. We can see that for all models the Clark and West (2007) test is able to reject the null that the gamma coefficient in Table 3 is zero at short horizons (one and six months ahead), providing evidence in favor of the predictive ability of the international factor. In addition, in most of our specifications the Giacomini and White (2006) test allows us to reject the null in favor of the method that includes the international factor. It is interesting to note that the Clark and West statistic is always higher than the Giacomini and White (2006) statistic. This is due to the correction for parameter uncertainty that is present in the derivation of the test by Clark and West.

Table 11
Test of Predictive Ability (R=80)
Up: RSMEP [t-stat. Clark and West (2007)], Down: [t-stat. Giacomini and White (2006)]

	LA FACTOR				OECD FACTOR			
	h=1	**h=6**	**h=12**	**h=24**	**h=1**	**h=6**	**h=12**	**h=24**
FS [1]	**0.442 [3.607]**	**1.710 [2.686]**	**3.025 [3.188]**	**3.510 [2.987]**	**0.446 [3.005]**	**1.884 [2.411]**	**3.193 [2.353]**	**3.597 [2.385]**
	[2.560]	**[2.180]**	**[2.076]**	**[1.922]**	**[2.154]**	**[2.002]**	**[1.670]**	**[1.912]**
FS [2]	**0.388 [3.563]**	**1.610 [2.740]**	**2.697 [2.104]**	2.892 [-0.848]	**0.375 [3.533]**	**1.627 [2.403]**	**2.700 [1.866]**	2.837 [-1.385]
	[1.804]	**[1.534]**	[0.939]	[-1.903]	**[2.372]**	**[1.949]**	**[1.415]**	[-1.826]
FS [3]	**0.372 [4.099]**	**1.615 [2.342]**	**2.823 [2.766]**	**3.151 [2.301]**	**0.367 [3.870]**	**1.685 [2.427]**	**2.877 [2.840]**	**3.100 [2.455]**
	[2.942]	**[1.681]**	**[1.456]**	[0.896]	**[3.232]**	**[1.436]**	[1.259]	**[1.355]**
FS [4]	**0.351 [3.737]**	**1.531 [2.363]**	2.584 [1.160]	2.687 [-0.339]	**0.351 [3.229]**	**1.557 [2.293]**	2.560 [0.974]	2.605 [-0.320]
	[2.093]	[1.144]	[-0.029]	[-1.947]	**[2.485]**	**[1.820]**	[0.568]	[-0.778]
FS [5]	**0.356 [3.745]**	**1.538 [2.540]**	**2.610 [1.436]**	2.682 [0.002]	**0.362 [3.188]**	**1.558 [2.403]**	**2.507 [2.393]**	2.600 [0.696]
	[2.101]	[1.229]	[0.181]	[-1.697]	**[1.834]**	[1.143]	**[1.736]**	[-0.311]
FS [6]	**0.372 [2.913]**	**1.573 [2.263]**	**2.678 [1.531]**	2.877 [-0.823]	**0.355 [3.952]**	**1.595 [2.033]**	**2.686 [1.403]**	2.852 [-1.225]
	[0.694]	[0.847]	[0.096]	[-2.286]	**[2.590]**	[0.636]	[-0.014]	[-2.131]
FS [7]	**0.360 [3.092]**	**1.517 [2.036]**	**2.611 [1.218]**	2.712 [0.179]	**0.351 [3.873]**	**1.483 [2.329]**	**2.512 [1.290]**	2.644 [0.065]
	[0.867]	[0.484]	[-0.437]	[-2.476]	**[2.139]**	**[1.461]**	[0.578]	[-2.412]
FS [8]	**0.441 [4.243]**	**1.751 [2.643]**	**3.057 [3.155]**	**3.516 [2.955]**	**0.455 [2.943]**	**1.933 [2.285]**	**3.280 [1.972]**	**3.666 [1.938]**
	[2.869]	**[2.162]**	**[2.152]**	**[2.028]**	**[1.748]**	**[1.701]**	[0.937]	[1.222]
FS [9]	**0.448 [3.559]**	**1.656 [2.729]**	**2.983 [3.044]**	**3.503 [2.843]**	**0.446 [2.774]**	**1.809 [2.237]**	**3.139 [2.283]**	**3.550 [2.320]**
	[2.391]	**[2.225]**	**[2.037]**	**[1.879]**	**[2.325]**	**[1.911]**	**[1.553]**	**[1.822]**
FS [10]	**0.451 [2.752]**	**1.666 [2.528]**	**2.976 [3.033]**	**3.456 [2.839]**	**0.452 [2.792]**	**1.825 [2.429]**	**3.106 [2.533]**	**3.457 [2.463]**
	[2.269]	**[2.075]**	**[1.950]**	**[1.635]**	**[2.378]**	**[1.921]**	**[1.648]**	**[1.822]**

Notes: Figures without brackets show the Clark and West (2007) core statistic. Figures in brackets show the t-statistics for the Clark and West (2007) test (upper level) and for the Giacomini and White (2006) test (lower level). Shaded cells indicate statistically significant results at the 10% level. FASARIMA models are computed using the Simple Average as international factor.

Source: Authors' elaboration

When focusing on the Giacomini and White (2006) test, we see that at short horizons (1 month) this test rejects the null of superior predictive ability of the univariate strategy in favor of the augmented specification for all the models when using the OECD factor. Similar results are obtained for the factor with LA countries, but in this case the tests reject in eight out of ten models. We would like to mention that we are using the unconditional version of the Giacomini and White (2006) test which is very similar to the traditional test attributed to Diebold and Mariano (1995) and West (1996).

ii. A Perfect Foresight Exercise

Our previous evaluation of the ability that an international factor may have to predict local inflation relies, at least for long horizons, on the ability that equation (2) may have to correctly forecast the corresponding international factor. If this expression (2) is a poor representation of the international factor, then a failure to detect predictability may be originated in a misspecification issue and not on a lack of predictability per se. We notice that this is only a potential problem when forecasting at horizons longer than 1 month. When forecasts are made one-step-ahead, equation (2) is no longer necessary so misspecifications concerns are of no relevance. Another technical issue that we need to consider when carrying out inference at longer horizons is that it is not clear whether size and power properties of the normal approximation for the Clark and West (2007) test are adequate. This is so because this approximation was introduced in the context of direct multi-step forecasts and not in the context of the iterated method to construct multistep forecasts that we use here. In this regard, the use of normal critical values for the Clark and West (2007) t-statistics shown in Table 11 might not be adequate for multistep forecasts.

One way to deal with the shortcomings associated with our multistep forecasts is to carry out a perfect foresight exercise in which multistep forecasts are built using our 10 FASARIMA expressions but assuming that future values of the international factors are known. These conditional forecasts would indicate if knowledge of a particular set of information about the future would be helpful to build better forecasts. Table 12 shows the RMSPE ratio between forecasts based upon the true path of the international factor and forecasts built with the aid of expression (2). Interestingly, all figures are below one (with the obvious exception of the first forecasting horizon, for which the ratio is one for construction) indicating that accurate knowledge of the future international factor would improve the local forecasts. These results corroborate our previous in-sample and out-of sample findings indicating that the international inflation factors are useful for forecasting Chilean Inflation.

Table 12
Multi-horizon RMSPE Ratios Between Perfect Foresight Forecasts and Iterated Forecasts
Rolling Windows of 80 Observations

	LA Factor					**OECD Factor**				
	h=1	**h=3**	**h=6**	**h=12**	**h=24**	**h=1**	**h=3**	**h=6**	**h=12**	**h=24**
FS [1] Forecast	1.00	0.94	0.91	0.86	0.90	1.00	0.95	0.93	0.92	0.94
FS [2] Forecast	1.00	0.95	0.92	0.90	0.91	1.00	0.90	0.82	0.81	0.83
FS [3] Forecast	1.00	0.93	0.88	0.84	0.88	1.00	0.89	0.82	0.81	0.86
FS [4] Forecast	1.00	0.95	0.92	0.91	0.95	1.00	0.94	0.90	0.89	0.91
FS [5] Forecast	1.00	0.95	0.92	0.90	0.94	1.00	0.96	0.92	0.94	0.95
FS [6] Forecast	1.00	0.94	0.92	0.91	0.93	1.00	0.92	0.85	0.85	0.87
FS [7] Forecast	1.00	0.96	0.94	0.92	0.95	1.00	0.93	0.86	0.84	0.86
FS [8] Forecast	1.00	0.94	0.91	0.88	0.91	1.00	0.95	0.93	0.93	0.94
FS [9] Forecast	1.00	0.94	0.90	0.83	0.85	1.00	0.93	0.88	0.85	0.88
FS [10] Forecast	1.00	0.93	0.88	0.81	0.85	1.00	0.91	0.86	0.82	0.86

Notes: Figures less than 1 favors forecasts built with known values of future international inflation factors.

Source: Authors' elaboration

Table 13 below shows sample RMSPE when forecasting with and without the international factor. This table reveals that there is an important amount of uncertainty surrounding Chilean inflation forecasts even at relatively short horizons. For instance, six months ahead, the expected RMSPE is about 180 basis points with univariate forecasts, and about 170 basis points when using the univariate model augmented with the international factor. Consequently, even with the aid of the global factor, forecasting uncertainty regarding Chilean Inflation is still high.

Table 13
Multi-horizon RMSPE Perfect Foresight Forecasts, Iterated Forecasts and Univariate models
Rolling Windows of 80 Observations

Simple Average of international Inflation is used as a Factor

	LATAM Factor					OECD Factor				
	h=1	**h=3**	**h=6**	**h=12**	**h=24**	**h=1**	**h=3**	**h=6**	**h=12**	**h=24**
FS [1] Perfect Foresight	0.442	0.942	1.555	2.610	3.148	0.446	1.010	1.749	2.935	3.397
FS [1] Forecast	0.442	1.001	1.710	3.025	3.510	0.446	1.062	1.884	3.193	3.597
S [1]	0.481	1.174	2.052	3.371	3.868	0.481	1.174	2.052	3.371	3.868
FS [2] Perfect Foresight	0.388	0.881	1.477	2.431	2.619	0.375	0.813	1.339	2.191	2.367
FS [2] Forecast	0.388	0.931	1.610	2.697	2.892	0.375	0.907	1.627	2.700	2.837
S [2]	0.430	1.037	1.778	2.819	2.706	0.430	1.037	1.778	2.819	2.706
FS [3] Perfect Foresight	0.372	0.854	1.418	2.366	2.779	0.367	0.830	1.386	2.330	2.657
FS [3] Forecast	0.372	0.923	1.615	2.823	3.151	0.367	0.931	1.685	2.877	3.100
S [3]	0.425	1.092	1.879	3.051	3.314	0.425	1.092	1.879	3.051	3.314
FS [4] Perfect Foresight	0.351	0.834	1.414	2.351	2.544	0.351	0.819	1.395	2.285	2.368
FS [4] Forecast	0.351	0.880	1.531	2.584	2.687	0.351	0.873	1.557	2.560	2.605
S [4]	0.377	0.931	1.612	2.581	2.581	0.377	0.931	1.612	2.581	2.581
FS [5] Perfect Foresight	0.356	0.833	1.413	2.345	2.532	0.362	0.845	1.437	2.354	2.470
FS [5] Forecast	0.356	0.879	1.538	2.610	2.682	0.362	0.883	1.558	2.507	2.600
S [5]	0.385	0.931	1.612	2.628	2.587	0.385	0.931	1.612	2.628	2.587
FS [6] Perfect Foresight	0.372	0.852	1.444	2.427	2.687	0.355	0.801	1.361	2.272	2.467
FS [6] Forecast	0.372	0.904	1.573	2.678	2.877	0.355	0.876	1.595	2.686	2.852
S [6]	0.381	0.923	1.621	2.685	2.703	0.381	0.923	1.621	2.685	2.703
FS [7] Perfect Foresight	0.360	0.837	1.423	2.400	2.582	0.351	0.773	1.269	2.118	2.277
FS [7] Forecast	0.360	0.873	1.517	2.611	2.712	0.351	0.832	1.483	2.512	2.644
S [7]	0.372	0.892	1.555	2.558	2.569	0.372	0.892	1.555	2.558	2.569
FS [8] Perfect Foresight	0.441	0.959	1.602	2.682	3.198	0.455	1.037	1.800	3.035	3.435
FS [8] Forecast	0.441	1.018	1.751	3.057	3.516	0.455	1.087	1.933	3.280	3.666
S [8]	0.483	1.188	2.069	3.383	3.857	0.483	1.188	2.069	3.383	3.857
FS [9] Perfect Foresight	0.448	0.918	1.483	2.480	2.990	0.446	0.945	1.586	2.655	3.117
FS [9] Forecast	0.448	0.974	1.656	2.983	3.503	0.446	1.016	1.809	3.139	3.550
S [9]	0.486	1.143	2.032	3.391	3.931	0.486	1.143	2.032	3.391	3.931
FS [10] Perfect Foresight	0.451	0.917	1.473	2.422	2.923	0.452	0.940	1.568	2.540	2.971
FS [10] Forecast	0.451	0.981	1.666	2.976	3.456	0.452	1.033	1.825	3.106	3.457
S [10]	0.540	1.243	2.123	3.401	3.828	0.540	1.243	2.123	3.401	3.828

Notes: S[j] represents RMSPE of the univariate model j en table 3. FS[j] corresponds to the RMSPE of the same model but augmented with the international factor and expression (3).
Source: Authors' elaboration

iii. What factors and countries should we use?

Table 3 in the appendix shows RMSPE when forecasting with our univariate methods and when forecasting with these methods extended with the three different international factors that we consider. From this table we can see that the simple average in general displays the best performance across the different methodologies at short horizons. At longer horizons, either Partial Least Squares or Principal Components perform better.

From Table 3 in the appendix we can also detect that the behavior of OECD versus LA factors is heterogeneous. When using principal components, OECD factors work better than LA factors. On the contrary, when using the simple average or partial least squares, LA countries perform better. The overall minima are obtained using the simple average and the OECD countries for horizons of 1, 6, 12 and 18 months ahead. When forecasting at 24 months ahead a modest edge in favor of partial least squares using LA countries is detected.

As a final exercise we also construct two additional international factors taking the simple average and a weighted average of the 15 countries that explain on average about 80% of Chilean imports since 2000. These countries are: US, China, Argentina, Brazil, South Korea, Germany, Japan, Mexico, Peru, Colombia, Spain, Ecuador, France, Italy and Canada. Weights are proportional to the share of imports coming from a given country. Table 14 next shows RMSPE ratios between forecasts coming from the FASARIMA models constructed with the "imports factor" against those constructed with the simple average of OECD countries. Table 14 displays figures mostly above 1 favoring the simple average factor of OECD countries. This result suggests that something else than a pure trading channel may be explaining the interesting predictive results that we have shown in this paper. We notice, however, that forecasts with the imported factor tend to outperform pure univariate models, which might suggest that the trade channel is part of the story behind our results.

Table 14
Multi-horizon RMSPE ratios between "Imported-factor" Forecasts and Simple Average of OECD countries
Rolling Windows of 80 Observations

	f [Mean_15_Impo]				
FS [1]	1.01	1.03	1.04	1.05	1.06
FS [2]	1.08	1.05	1.03	1.06	1.10
FS [3]	1.04	1.04	1.03	1.06	1.10
FS [4]	1.02	1.01	0.99	1.02	1.05
FS [5]	1.01	1.04	1.03	1.05	1.04
FS [6]	1.05	1.05	1.04	1.07	1.10
FS [7]	1.04	1.03	1.02	1.04	1.06
FS [8]	1.01	1.01	1.03	1.06	1.08
FS [9]	1.01	1.01	1.01	1.04	1.06
FS [10]	1.02	1.01	1.02	1.05	1.07

	f [Weighted_Mean_15_Impo]				
FS [1]	1.06	1.07	1.06	1.04	1.06
FS [2]	1.17	1.13	1.09	1.04	0.98
FS [3]	1.20	1.14	1.08	1.04	1.07
FS [4]	1.10	1.07	1.04	1.01	0.99
FS [5]	1.12	1.07	1.04	1.11	1.09
FS [6]	1.10	1.05	1.02	1.01	0.95
FS [7]	1.07	1.05	1.03	1.01	0.97
FS [8]	1.07	1.07	1.05	1.01	1.05
FS [9]	1.07	1.07	1.06	1.03	1.07
FS [10]	1.16	1.13	1.10	1.05	1.08

Notes: figures less than 1 favor the use of the simple average of OECD countries as international inflation factor.

V. Summary and Conclusions

In this paper we use monthly CPI data for a number of countries during the sample period January 1995-March 2013 to build forecasts for Chilean year-on-year inflation. These forecasts are built using simple time-series models augmented with different measures of international inflation. Broadly speaking, we construct two families of international inflation factors using three different methodologies: simple average, partial least squares and principal components. The first family is built applying these three techniques to year-on-year inflation of 18 Latin American countries (excluding Chile). The second family is built applying these three techniques to year-on-year inflation of 30 OECD countries (excluding Chile). We show sound in-sample and out-of-sample evidence indicating that these six international factors do help forecast Chilean inflation at several horizons. In general, with only a few exceptions, incorporating the international factors reduce the Root Mean Squared Prediction Error of pure univariate SARIMA models. We carry out our out-of-sample analysis using rolling estimation windows of 50 and 80 observations. As expected, results in favor of the predictive ability of the international factor are stronger when the size of the estimation window is larger.

We also show that the simple average in general displays the best performance across the different methodologies at short horizons. At longer horizons, either Partial Least Squares or Principal Components perform better.

The behavior of OECD versus LA factors is heterogeneous. When using principal components, OECD factors work better than LA factors. On the contrary, when using the simple average or partial least squares, LA countries perform better.

We think that the set of findings reported in this paper are both interesting and useful for forecasting purposes. Nevertheless, a number of questions arise or are still unresolved. One interesting issue to consider is the jump in the predictive marginal effect of our international factors by the end of the last decade. This increment coincides with the post crisis period. In addition, the way that Chilean CPI was measured suffered important changes during that period. We think that the analysis of the causes underlying this increment deserves further attention. In particular it would be interesting to know if other countries follow a similar pattern. More generally, one important issue to address is the question about the economic reasons behind the ability of the international factor to predict local Chilean Inflation during the whole sample period. One may think that potential drivers are commodity prices that tend to move together and that might pose inflationary pressures. We have also mentioned that a trading channel might be part of the story as well. The increasing implementation of inflation targeting regimes in several countries might also lead to an implicit international policy coordination. All these questions are left unanswered, and hopefully will be addressed in future research. As a final remark, it is important to emphasize that irrespective of the economic reasons underlying our results, our measures of international inflation may be capturing the impact of all these economic forces in just one variable. It is perfectly possible that in some periods domestic inflation may be driven by commodity shocks. But it is also possible that in some other periods domestic inflation may be driven by either aggregate demand shocks or international monetary policy shocks. It is within this plethora of different economic forces that the identification of one single factor (international inflation) capturing several different transmission channels is relevant and useful for forecasting purposes.

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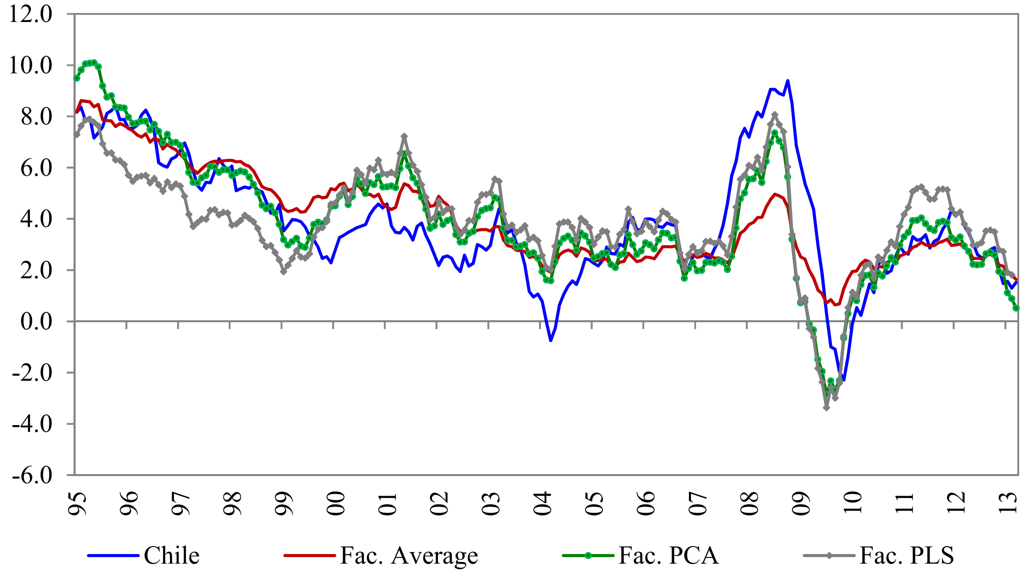
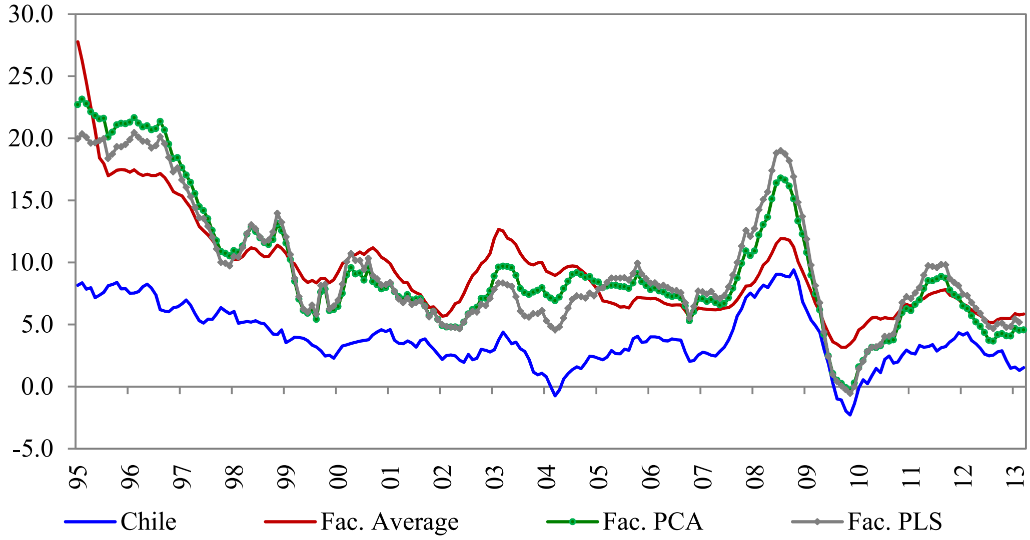
Appendix

Figure 1
Inflation in Chile and International Inflation Factors Based on OECD Economies
1995:01 – 2013:03



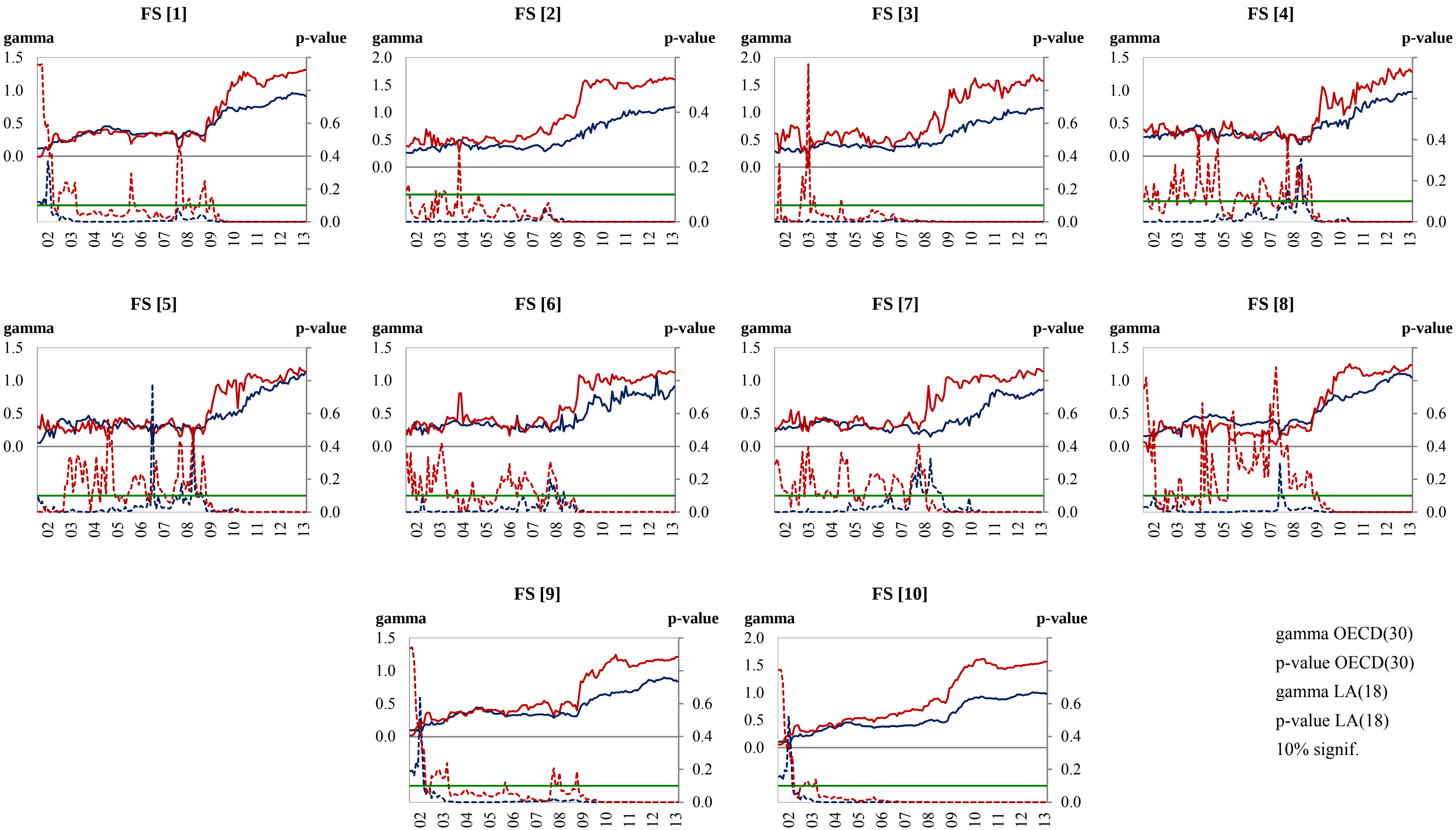
Source: Authors’ elaboration

Figure 2
Inflation in Chile and International Inflation Factors Based on LA Countries
1995:01 – 2013:03



Source: Authors' elaboration

Figure 3
Chile: Evolution of the Parameter and p-value Associated to Global Inflation Factor estimated by the Average
(FASARIMA Models, R=80)



Note: The picture shows the evolution of the gamma (solid line) for each estimation window of 80 observations. The first estimation window was the period 1995:01 - 2001:08 while the final estimation window was the period 2006:07 - 2013:02. The p-value of the estimated gamma shown in dashed line, thus increasing the dashed line is below the green line, the gamma is statistically significant at 10% level. **Source:** Authors' elaboration.

Table 1
OECD (30): Descriptive Statistics

Country	First Estimation Sample Jan:1995 - Aug:2001				First Evaluation Sample Sep:2001 - Mar:2013				Full Sample Jan:1995 - Mar:2013			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Austria	1.66	0.83	-0.11	3.28	2.03	0.85	-0.28	3.78	1.89	0.86	-0.28	3.78
Belgium	1.71	0.68	0.35	3.24	2.20	1.25	-1.65	5.72	2.02	1.10	-1.65	5.72
Canada	1.91	0.77	0.59	3.87	1.95	0.95	-0.93	4.58	1.93	0.89	-0.93	4.58
Czech Republic	6.69	3.06	1.05	12.65	2.38	1.67	-0.42	7.27	3.96	3.08	-0.42	12.65
Denmark	2.27	0.44	1.52	3.26	2.07	0.69	0.82	4.18	2.14	0.62	0.82	4.18
Finland	1.51	0.97	-0.11	3.63	1.70	1.33	-1.56	4.60	1.63	1.21	-1.56	4.60
France	1.34	0.63	0.11	2.54	1.74	0.73	-0.66	3.53	1.59	0.72	-0.66	3.53
Germany	1.41	0.57	0.11	2.78	1.59	0.69	-0.47	3.23	1.52	0.66	-0.47	3.23
Greece	5.18	2.27	2.00	10.14	3.02	1.19	-0.24	5.44	3.81	1.96	-0.24	10.14
Hungary	15.21	6.00	8.21	27.09	5.04	1.52	2.16	8.68	8.76	6.21	2.16	27.09
Iceland	2.85	1.65	0.80	7.66	5.77	3.46	1.42	17.02	4.70	3.25	0.80	17.02
Ireland	2.77	1.59	0.93	6.73	2.20	2.76	-6.76	5.03	2.41	2.41	-6.76	6.73
Israel	6.14	3.86	-0.11	13.01	2.26	2.11	-2.83	6.67	3.68	3.42	-2.83	13.01
Italy	2.86	1.26	1.29	5.60	2.22	0.74	0.00	4.05	2.45	1.01	0.00	5.60
Japan	0.15	0.95	-1.16	2.53	-0.23	0.80	-2.57	2.27	-0.09	0.87	-2.57	2.53
Korea, Rep.	4.01	2.07	0.12	9.12	3.01	0.89	1.22	5.74	3.38	1.51	0.12	9.12
Luxembourg	1.71	0.93	-1.29	3.59	2.31	0.87	-0.64	4.69	2.09	0.94	-1.29	4.69
Mexico	18.29	9.55	5.72	41.85	4.28	0.79	2.87	6.32	9.40	8.90	2.87	41.85
Netherlands	2.28	0.68	1.38	4.33	1.96	0.81	0.19	4.16	2.08	0.78	0.19	4.33
Norway	2.41	0.70	0.61	4.29	1.72	1.17	-1.83	5.37	1.97	1.08	-1.83	5.37
Poland	13.25	6.44	4.88	28.92	2.71	1.30	0.11	4.75	6.56	6.48	0.11	28.92
Portugal	3.02	0.89	1.56	5.00	2.38	1.33	-1.76	4.10	2.61	1.23	-1.76	5.00
Slovak Republic	8.06	2.87	4.91	15.35	3.93	2.19	0.35	9.35	5.44	3.16	0.35	15.35
Slovenia	8.69	2.51	4.12	17.88	3.46	2.04	-0.62	8.07	5.37	3.36	-0.62	17.88
Spain	3.01	1.04	1.36	5.21	2.69	1.22	-1.35	5.15	2.81	1.17	-1.35	5.21
Sweden	0.93	1.05	-1.20	2.79	1.48	1.27	-1.86	4.32	1.28	1.22	-1.86	4.32
Switzerland	0.95	0.64	-0.21	2.08	0.62	0.90	-1.25	3.10	0.74	0.83	-1.25	3.10
Turkey	55.19	10.47	28.86	82.67	12.89	11.49	3.89	54.85	28.34	23.24	3.89	82.67
United Kingdom	1.71	0.66	0.54	2.93	2.39	1.04	0.63	5.12	2.14	0.98	0.54	5.12
United States	2.57	0.65	1.37	3.69	2.34	1.34	-2.12	5.45	2.42	1.14	-2.12	5.45

Source: Authors' elaboration.

Table 2
LA (19): Descriptive Statistics

Country	First Estimation Sample Jan:1995 - Aug:2001				First Evaluation Sample Sep:2001 - Mar:2013				Full Sample Jan:1995 - Mar:2013			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Argentina	0.34	1.60	-2.05	4.92	9.77	6.77	-1.76	34.32	6.32	7.12	-2.05	34.32
Bolivia	6.24	3.59	1.02	14.72	5.21	3.71	-1.27	15.97	5.59	3.69	-1.27	15.97
Brazil	16.21	33.15	2.26	199.99	6.62	3.39	2.56	18.60	10.12	20.67	2.26	199.99
Chile	5.32	1.78	2.28	8.40	3.10	2.23	-2.29	9.40	3.91	2.34	-2.29	9.40
Colombia	14.45	4.63	7.52	19.79	4.83	1.68	1.81	7.70	8.34	5.58	1.81	19.79
Costa Rica	13.15	4.02	7.27	22.26	8.81	3.14	2.53	15.10	10.39	4.06	2.53	22.26
Dominican Republic	7.55	2.76	2.85	14.21	10.41	11.76	-1.58	50.25	9.36	9.60	-1.58	50.25
Ecuador	35.12	16.00	19.87	73.18	5.53	4.16	1.38	24.06	16.34	17.54	1.38	73.18
El Salvador	4.67	3.64	-1.20	11.50	3.24	2.26	-1.61	9.43	3.77	2.92	-1.61	11.50
Guatemala	7.32	2.32	-0.53	11.92	6.25	2.71	-0.73	13.24	6.64	2.62	-0.73	13.24
Haiti	14.45	5.25	7.12	30.66	11.81	8.52	-4.77	35.39	12.77	7.59	-4.77	35.39
Honduras	15.95	6.21	8.85	28.99	6.90	2.06	2.62	13.10	10.20	5.98	2.62	28.99
Mexico	18.29	9.55	5.72	41.85	4.28	0.79	2.87	6.32	9.40	8.90	2.87	41.85
Nicaragua	10.38	2.23	6.77	16.94	7.86	4.22	-0.12	21.45	8.78	3.81	-0.12	21.45
Panama	1.05	0.58	-0.45	2.29	3.29	2.48	-0.96	9.57	2.47	2.28	-0.96	9.57
Paraguay	8.94	2.82	4.23	15.58	7.10	3.81	1.13	19.05	7.77	3.59	1.13	19.05
Peru	6.85	3.24	1.36	12.86	2.51	1.66	-1.12	6.53	4.10	3.16	-1.12	12.86
Uruguay	15.35	11.32	3.32	37.39	8.45	4.64	3.37	25.08	10.97	8.43	3.32	37.39
Venezuela	34.93	19.58	11.38	76.63	20.59	5.24	9.87	32.70	25.82	14.29	9.87	76.63

Source: Authors' elaboration

Table 3: Chile: Multi-horizon RMSPE Estimates (R=80)

	Factorial LA(18)					Factorial OECD(30)				
	h=1	**h=3**	**h=6**	**h=12**	**h=24**	**h=1**	**h=3**	**h=6**	**h=12**	**h=24**
Mean FASARIMAS	**0.413**	**0.971**	**1.669**	**2.849**	**3.160**	**0.405**	**0.969**	**1.708**	**2.851**	**3.099**
Mean FS (A)	0.398	0.936	1.617	2.804	3.099	0.396	0.950	1.696	2.856	3.091
Mean FS (PCA)	0.418	0.985	1.722	2.993	3.278	0.399	0.949	1.681	2.827	3.080
Mean FS (PLS)	0.418	0.982	1.660	2.741	3.136	0.421	1.008	1.744	2.868	3.145
Mean SARIMAS	**0.436**	**1.055**	**1.833**	**2.987**	**3.194**	**0.436**	**1.055**	**1.833**	**2.987**	**3.194**
SIMPLE AVERAGE (SA)										
FS [1]	0.442	1.001	1.710	3.025	3.510	0.446	1.062	1.884	3.193	3.597
FS [2]	0.388	0.931	1.610	2.697	2.892	0.375	0.907	1.627	2.700	2.837
FS [3]	0.372	0.923	1.615	2.823	3.151	0.367	0.931	1.685	2.877	3.100
FS [4]	0.351	0.880	1.531	2.584	2.687	0.351	0.873	1.557	2.560	2.605
FS [5]	0.356	0.879	1.538	2.610	2.682	0.362	0.883	1.558	2.507	2.600
FS [6]	0.372	0.904	1.573	2.678	2.877	0.355	0.876	1.595	2.686	2.852
FS [7]	0.360	0.873	1.517	2.611	2.712	0.351	0.832	1.483	2.512	2.644
FS [8]	0.441	1.018	1.751	3.057	3.516	0.455	1.087	1.933	3.280	3.666
FS [9]	0.448	0.974	1.656	2.983	3.503	0.446	1.016	1.809	3.139	3.550
FS [10]	0.451	0.981	1.666	2.976	3.456	0.452	1.033	1.825	3.106	3.457
PRINCIPAL COMPONENTS ANALYSIS (PCA)										
FS [1]	0.463	1.103	1.948	3.371	3.795	0.449	1.060	1.856	3.165	3.663
FS [2]	0.424	0.998	1.682	2.889	2.856	0.378	0.912	1.626	2.689	2.782
FS [3]	0.392	0.957	1.717	3.073	3.499	0.372	0.930	1.660	2.806	3.056
FS [4]	0.367	0.873	1.511	2.521	2.604	0.362	0.894	1.580	2.580	2.584
FS [5]	0.372	0.886	1.533	2.534	2.560	0.367	0.899	1.588	2.604	2.582
FS [6]	0.379	0.910	1.582	2.705	2.922	0.364	0.876	1.587	2.690	2.867
FS [7]	0.369	0.870	1.496	2.533	2.754	0.354	0.844	1.502	2.508	2.576
FS [8]	0.465	1.119	1.976	3.372	3.787	0.457	1.068	1.885	3.206	3.651
FS [9]	0.470	1.060	1.874	3.435	4.012	0.440	0.990	1.750	3.024	3.555
FS [10]	0.481	1.076	1.904	3.498	3.990	0.447	1.016	1.778	2.997	3.487
PARTIAL LEAST SQUARES (PLS)										
FS [1]	0.459	1.043	1.766	3.023	3.592	0.468	1.101	1.909	3.223	3.702
FS [2]	0.417	0.987	1.651	2.578	2.825	0.416	0.997	1.705	2.730	2.875
FS [3]	0.396	0.950	1.592	2.659	3.109	0.403	0.986	1.694	2.792	3.021
FS [4]	0.365	0.941	1.607	2.580	2.788	0.371	0.957	1.657	2.674	2.770
FS [5]	0.369	0.936	1.600	2.558	2.777	0.380	0.959	1.668	2.653	2.795
FS [6]	0.381	0.945	1.609	2.572	2.852	0.381	0.948	1.648	2.670	2.839
FS [7]	0.379	0.930	1.589	2.531	2.750	0.377	0.933	1.625	2.606	2.744
FS [8]	0.461	1.060	1.813	3.072	3.592	0.472	1.093	1.904	3.221	3.664
FS [9]	0.468	1.006	1.677	2.936	3.588	0.463	1.038	1.802	3.069	3.557
FS [10]	0.485	1.023	1.692	2.904	3.486	0.479	1.071	1.833	3.044	3.485
BENCHMARK										
S [1]	0.481	1.174	2.052	3.371	3.868	0.481	1.174	2.052	3.371	3.868
S [2]	0.430	1.037	1.778	2.819	2.706	0.430	1.037	1.778	2.819	2.706
S [3]	0.425	1.092	1.879	3.051	3.314	0.425	1.092	1.879	3.051	3.314
S [4]	0.377	0.931	1.612	2.581	2.581	0.377	0.931	1.612	2.581	2.581
S [5]	0.385	0.931	1.612	2.628	2.587	0.385	0.931	1.612	2.628	2.587
S [6]	0.381	0.923	1.621	2.685	2.703	0.381	0.923	1.621	2.685	2.703
S [7]	0.372	0.892	1.555	2.558	2.569	0.372	0.892	1.555	2.558	2.569
S [8]	0.483	1.188	2.069	3.383	3.857	0.483	1.188	2.069	3.383	3.857
S [9]	0.486	1.143	2.032	3.391	3.931	0.486	1.143	2.032	3.391	3.931
S [10]	0.540	1.243	2.123	3.401	3.828	0.540	1.243	2.123	3.401	3.828

Source: Authors' elaboration

Table 4
Chile: RMSEP of the FASARIMA model relative to the SARIMA model
(R=80)

	LA Factor					OECD Factor				
	h=1	**h=3**	**h=6**	**h=12**	**h=24**	**h=1**	**h=3**	**h=6**	**h=12**	**h=24**
				Mean RSMEP FASARIMAS vs. Mean RSMEP SARIMAS						
FS (A) vs. SARIMAS	0.913	0.887	0.882	0.939	0.970	0.908	0.900	0.925	0.956	0.968
FS (PCA) vs. SARIMAS	0.959	0.933	0.939	1.002	1.026	0.915	0.899	0.917	0.946	0.964
FS (PLS) vs. SARIMAS	0.959	0.930	0.905	0.918	0.982	0.966	0.956	0.951	0.960	0.985
					AVERAGE (A)					
FS [1] vs. S [1]	0.918	0.852	0.833	0.897	0.907	0.927	0.905	0.918	0.947	0.930
FS [2] vs. S [2]	0.901	0.898	0.906	0.957	1.069	0.871	0.875	0.915	0.958	1.049
FS [3] vs. S [3]	0.877	0.845	0.859	0.925	0.951	0.863	0.853	0.896	0.943	0.935
FS [4] vs. S [4]	0.930	0.945	0.950	1.001	1.041	0.931	0.937	0.966	0.992	1.009
FS [5] vs. S [5]	0.924	0.944	0.954	0.993	1.037	0.940	0.949	0.966	0.954	1.005
FS [6] vs. S [6]	0.976	0.980	0.970	0.997	1.064	0.933	0.949	0.984	1.000	1.055
FS [7] vs. S [7]	0.970	0.978	0.976	1.021	1.056	0.943	0.933	0.954	0.982	1.029
FS [8] vs. S [8]	0.913	0.857	0.846	0.904	0.912	0.942	0.915	0.934	0.970	0.950
FS [9] vs. S [9]	0.922	0.853	0.815	0.880	0.891	0.918	0.889	0.890	0.926	0.903
FS [10] vs. S [10]	0.835	0.790	0.785	0.875	0.903	0.837	0.831	0.860	0.913	0.903
					PRINCIPAL COMPONENTS ANALYSIS (PCA)					
FS [1] vs. S [1]	0.963	0.939	0.949	1.000	0.981	0.934	0.902	0.905	0.939	0.947
FS [2] vs. S [2]	0.986	0.962	0.946	1.025	1.055	0.879	0.880	0.914	0.954	1.028
FS [3] vs. S [3]	0.923	0.876	0.914	1.007	1.056	0.877	0.851	0.883	0.919	0.922
FS [4] vs. S [4]	0.972	0.938	0.938	0.977	1.009	0.959	0.960	0.981	1.000	1.001
FS [5] vs. S [5]	0.967	0.952	0.951	0.964	0.990	0.954	0.965	0.985	0.991	0.998
FS [6] vs. S [6]	0.995	0.986	0.976	1.008	1.081	0.954	0.949	0.979	1.002	1.061
FS [7] vs. S [7]	0.994	0.976	0.962	0.990	1.072	0.954	0.946	0.966	0.980	1.003
FS [8] vs. S [8]	0.962	0.942	0.955	0.997	0.982	0.944	0.898	0.911	0.948	0.946
FS [9] vs. S [9]	0.967	0.928	0.922	1.013	1.020	0.907	0.866	0.861	0.892	0.904
FS [10] vs. S [10]	0.890	0.866	0.897	1.029	1.042	0.828	0.817	0.837	0.881	0.911
					PARTIAL LEAST SQUARES (PLS)					
FS [1] vs. S [1]	0.953	0.888	0.861	0.897	0.929	0.973	0.937	0.930	0.956	0.957
FS [2] vs. S [2]	0.968	0.952	0.929	0.915	1.044	0.968	0.961	0.959	0.968	1.063
FS [3] vs. S [3]	0.934	0.869	0.847	0.871	0.938	0.950	0.903	0.901	0.915	0.912
FS [4] vs. S [4]	0.969	1.011	0.997	1.000	1.080	0.984	1.028	1.028	1.036	1.073
FS [5] vs. S [5]	0.958	1.006	0.993	0.974	1.073	0.986	1.031	1.035	1.010	1.080
FS [6] vs. S [6]	1.000	1.024	0.993	0.958	1.055	1.001	1.028	1.016	0.994	1.050
FS [7] vs. S [7]	1.020	1.043	1.022	0.990	1.070	1.016	1.046	1.045	1.019	1.068
FS [8] vs. S [8]	0.954	0.892	0.876	0.908	0.931	0.976	0.920	0.920	0.952	0.950
FS [9] vs. S [9]	0.963	0.880	0.825	0.866	0.913	0.954	0.908	0.886	0.905	0.905
FS [10] vs. S [10]	0.898	0.823	0.797	0.854	0.911	0.888	0.862	0.863	0.895	0.910
FASARIMAS (10 Mod.)										
SA: # Ratios<1	10	10	10	8	5	10	10	10	9	5
PCA: # Ratios<1	10	10	10	4	3	10	10	10	9	6
PLS: # Ratios<1	8	6	9	10	5	8	6	6	7	5

Note: The table presents the ratio of RSMEP between FASARIMA and SARIMA models. Figures below 1 favor models with the international factor. Shaded cells highlight figures below or equal to 1. In the end of the table we show the total number of ratios below1.
Source: Authors' elaboration

Table 5
Test of Equality Predictive Ability (R=80)
Up: RSMEP [t-stat. Clark and West (2007)], Down: [t-stat. Giacomini and White (2006)]

	LA Factors					OECD Factors				
	h=1	**h=3**	**h=6**	**h=12**	**h=24**	**h=1**	**h=3**	**h=6**	**h=12**	**h=24**
FS [1]										
SA:	0.442 [3.607]	1.001 [2.774]	1.710 [2.686]	3.025 [3.188]	3.510 [2.987]	0.446 [3.005]	1.062 [2.526]	1.884 [2.411]	3.193 [2.353]	3.597 [2.385]
	[2.560]	[2.207]	[2.180]	[2.076]	[1.922]	[2.154]	[2.267]	[2.002]	[1.670]	[1.912]
PCA:	0.463 [2.179]	1.103 [1.580]	1.948 [1.614]	3.371 [1.210]	3.795 [1.457]	0.449 [2.998]	1.060 [2.730]	1.856 [2.629]	3.165 [2.696]	3.663 [2.178]
	[1.573]	[1.284]	[1.062]	[-0.007]	[0.637]	[1.929]	[2.529]	[2.386]	[2.481]	[1.952]
PLS:	0.459 [2.336]	1.043 [2.237]	1.766 [2.179]	3.023 [2.267]	3.592 [2.083]	0.468 [2.173]	1.101 [2.523]	1.909 [2.576]	3.223 [2.393]	3.702 [1.933]
	[1.510]	[1.851]	[1.924]	[2.081]	[2.032]	[0.952]	[2.123]	[2.286]	[2.335]	[1.935]
S [1]	0.481	1.174	2.052	3.371	3.868	0.481	1.174	2.052	3.371	3.868
FS [2]										
SA:	0.388 [3.563]	0.931 [3.097]	1.610 [2.740]	2.697 [2.104]	2.892 [-0.848]	0.375 [3.533]	0.907 [3.043]	1.627 [2.403]	2.700 [1.866]	2.837 [-1.385]
	[1.804]	[1.614]	[1.534]	[0.939]	[-1.903]	[2.372]	[2.466]	[1.949]	[1.415]	[-1.826]
PCA:	0.424 [3.022]	0.998 [2.685]	1.682 [2.524]	2.889 [2.111]	2.856 [0.520]	0.378 [2.666]	0.912 [2.575]	1.626 [2.160]	2.689 [1.752]	2.782 [-1.408]
	[0.202]	[0.469]	[0.762]	[-0.485]	[-1.454]	[2.052]	[2.273]	[1.961]	[1.581]	[-1.599]
PLS:	0.417 [1.617]	0.987 [1.393]	1.651 [1.459]	2.578 [1.597]	2.825 [0.016]	0.416 [1.927]	0.997 [1.669]	1.705 [1.641]	2.730 [1.471]	2.875 [-0.773]
	[0.594]	[0.658]	[0.899]	[1.097]	[-0.707]	[1.029]	[0.991]	[1.045]	[0.815]	[-1.274]
S [2]	0.430	1.037	1.778	2.819	2.706	0.430	1.037	1.778	2.819	2.706
FS [3]										
SA:	0.372 [4.099]	0.923 [2.586]	1.615 [2.342]	2.823 [2.766]	3.151 [2.301]	0.367 [3.870]	0.931 [2.555]	1.685 [2.427]	2.877 [2.840]	3.100 [2.455]
	[2.942]	[1.997]	[1.681]	[1.456]	[0.896]	[3.232]	[2.021]	[1.436]	[1.259]	[1.355]
PCA:	0.392 [3.190]	0.957 [1.902]	1.717 [1.713]	3.073 [1.621]	3.499 [0.870]	0.372 [3.309]	0.930 [2.520]	1.660 [2.419]	2.806 [2.730]	3.056 [2.426]
	[2.201]	[1.530]	[1.028]	[-0.180]	[-0.944]	[2.753]	[2.083]	[1.677]	[1.786]	[1.913]
PLS:	0.396 [2.613]	0.950 [2.030]	1.592 [1.927]	2.659 [2.049]	3.109 [1.777]	0.403 [2.529]	0.986 [2.143]	1.694 [2.112]	2.792 [2.389]	3.021 [2.218]
	[1.369]	[1.414]	[1.461]	[1.653]	[1.317]	[1.494]	[1.554]	[1.524]	[1.895]	[2.098]
S [3]	0.425	1.092	1.879	3.051	3.314	0.425	1.092	1.879	3.051	3.314
FS [4]										
SA:	0.351 [3.737]	0.880 [2.951]	1.531 [2.363]	2.584 [1.160]	2.687 [-0.339]	0.351 [3.229]	0.873 [3.452]	1.557 [2.293]	2.560 [0.974]	2.605 [-0.320]
	[2.093]	[1.359]	[1.144]	[-0.029]	[-1.947]	[2.485]	[2.908]	[1.820]	[0.568]	[-0.778]
PCA:	0.367 [3.329]	0.873 [2.469]	1.511 [2.399]	2.521 [2.234]	2.604 [0.910]	0.362 [2.251]	0.894 [3.144]	1.580 [2.547]	2.580 [0.735]	2.584 [0.111]
	[1.319]	[1.390]	[1.470]	[0.811]	[-0.343]	[1.452]	[2.695]	[2.007]	[0.089]	[-0.196]
PLS:	0.365 [2.191]	0.941 [0.858]	1.607 [0.925]	2.580 [0.720]	2.788 [-0.667]	0.371 [1.776]	0.957 [0.035]	1.657 [-0.003]	2.674 [-0.099]	2.770 [-0.743]
	[0.944]	[-0.277]	[0.058]	[0.008]	[-1.245]	[0.566]	[-1.072]	[-0.929]	[-0.817]	[-1.227]
S [4]	0.377	0.931	1.612	2.581	2.581	0.377	0.931	1.612	2.581	2.581

Continue

	LA Factors					OECD Factors				
	h=1	h=3	h=6	h=12	h=24	h=1	h=3	h=6	h=12	h=24
FS [5]										
SA:	0.356 [3.745] [2.101]	0.879 [3.242] [1.579]	1.538 [2.540] [1.229]	2.610 [1.436] [0.181]	2.682 [0.002] [-1.697]	0.362 [3.188] [1.834]	0.883 [3.263] [1.657]	1.558 [2.403] [1.143]	2.507 [2.393] [1.736]	2.600 [0.696] [-0.311]
PCA:	0.372 [3.681] [1.408]	0.886 [2.847] [1.431]	1.533 [2.502] [1.399]	2.534 [2.565] [1.357]	2.560 [1.886] [0.469]	0.367 [2.425] [1.532]	0.899 [3.197] [2.303]	1.588 [2.375] [1.351]	2.604 [2.063] [1.343]	2.582 [0.610] [0.259]
PLS:	0.369 [2.378] [1.193]	0.936 [1.147] [-0.174]	1.600 [1.156] [0.171]	2.558 [1.199] [0.436]	2.777 [-0.503] [-1.108]	0.380 [2.203] [0.491]	0.959 [0.731] [-0.850]	1.668 [0.353] [-0.883]	2.653 [0.641] [-0.210]	2.795 [-0.821] [-1.350]
S [5]	0.385	0.931	1.612	2.628	2.587	0.385	0.931	1.612	2.628	2.587
FS [6]										
SA:	0.372 [2.913] [0.694]	0.904 [2.372] [0.520]	1.573 [2.263] [0.847]	2.678 [1.531] [0.096]	2.877 [-0.823] [-2.286]	0.355 [3.952] [2.590]	0.876 [2.749] [1.634]	1.595 [2.033] [0.636]	2.686 [1.403] [-0.014]	2.852 [-1.225] [-2.131]
PCA:	0.379 [2.695] [0.174]	0.910 [2.605] [0.534]	1.582 [2.360] [0.844]	2.705 [1.650] [-0.305]	2.922 [-1.425] [-3.262]	0.364 [2.427] [1.418]	0.876 [2.460] [1.628]	1.587 [1.989] [0.932]	2.690 [0.859] [-0.115]	2.867 [-2.154] [-2.460]
PLS:	0.381 [1.718] [-0.011]	0.945 [0.764] [-0.676]	1.609 [1.112] [0.197]	2.572 [1.398] [0.843]	2.852 [-0.521] [-1.100]	0.381 [1.583] [-0.048]	0.948 [0.057] [-1.201]	1.648 [0.323] [-0.821]	2.670 [0.998] [0.226]	2.839 [-0.647] [-1.124]
S [6]	0.381	0.923	1.621	2.685	2.703	0.381	0.923	1.621	2.685	2.703
FS [7]										
SA:	0.360 [3.092] [0.867]	0.873 [2.396] [0.454]	1.517 [2.036] [0.484]	2.611 [1.218] [-0.437]	2.712 [0.179] [-2.476]	0.351 [3.873] [2.139]	0.832 [2.942] [1.932]	1.483 [2.329] [1.461]	2.512 [1.290] [0.578]	2.644 [0.065] [-2.412]
PCA:	0.369 [3.153] [0.221]	0.870 [2.761] [0.630]	1.496 [2.605] [0.977]	2.533 [2.487] [0.262]	2.754 [0.225] [-1.935]	0.354 [2.664] [1.619]	0.844 [2.370] [1.673]	1.502 [2.106] [1.458]	2.508 [1.616] [1.174]	2.576 [0.001] [-0.360]
PLS:	0.379 [1.124] [-0.653]	0.930 [0.277] [-1.076]	1.589 [0.575] [-0.533]	2.531 [0.927] [0.165]	2.750 [-0.341] [-0.996]	0.377 [0.945] [-0.766]	0.933 [-0.263] [-1.360]	1.625 [-0.313] [-1.273]	2.606 [0.399] [-0.384]	2.744 [-0.410] [-1.008]
S [7]	0.372	0.892	1.555	2.558	2.569	0.372	0.892	1.555	2.558	2.569
FS [8]										
SA:	0.441 [4.243] [2.869]	1.018 [2.909] [2.311]	1.751 [2.643] [2.162]	3.057 [3.155] [2.152]	3.516 [2.955] [2.028]	0.455 [2.943] [1.748]	1.087 [2.504] [2.137]	1.933 [2.285] [1.701]	3.280 [1.972] [0.937]	3.666 [1.938] [1.222]
PCA:	0.465 [2.825] [1.939]	1.119 [1.691] [1.319]	1.976 [1.582] [0.993]	3.372 [1.359] [0.099]	3.787 [1.444] [0.617]	0.457 [2.977] [1.620]	1.068 [2.812] [2.542]	1.885 [2.669] [2.322]	3.206 [2.310] [2.020]	3.651 [1.907] [1.602]
PLS:	0.461 [2.591] [1.701]	1.060 [2.330] [1.921]	1.813 [2.115] [1.843]	3.072 [2.263] [2.060]	3.592 [2.068] [2.009]	0.472 [2.550] [0.865]	1.093 [2.884] [2.510]	1.904 [2.824] [2.548]	3.221 [2.228] [2.153]	3.664 [1.756] [1.736]
S [8]	0.483	1.188	2.069	3.383	3.857	0.483	1.188	2.069	3.383	3.857

Continue

	LA Factor					OECD Factor				
	h=1	h=3	h=6	h=12	h=24	h=1	h=3	h=6	h=12	h=24
FS [9]										
SA:	0.448 [3.559] [2.391]	0.974 [3.060] [2.328]	1.656 [2.729] [2.225]	2.983 [3.044] [2.037]	3.503 [2.843] [1.879]	0.446 [2.774] [2.325]	1.016 [2.161] [1.991]	1.809 [2.237] [1.911]	3.139 [2.283] [1.553]	3.550 [2.320] [1.822]
PCA:	0.470 [2.072] [1.568]	1.060 [1.756] [1.394]	1.874 [1.668] [1.132]	3.435 [1.204] [-0.266]	4.012 [0.731] [-0.373]	0.440 [2.747] [2.259]	0.990 [2.444] [2.360]	1.750 [2.518] [2.434]	3.024 [2.473] [2.238]	3.555 [2.228] [2.085]
PLS:	0.468 [2.575] [1.387]	1.006 [2.410] [1.867]	1.677 [2.240] [1.982]	2.936 [2.230] [2.059]	3.588 [1.922] [1.870]	0.463 [2.198] [1.677]	1.038 [2.346] [2.087]	1.802 [2.451] [2.393]	3.069 [2.289] [2.186]	3.557 [2.120] [2.182]
S [9]	0.486	1.143	2.032	3.391	3.931	0.486	1.143	2.032	3.391	3.931
FS [10]										
SA:	0.451 [2.752] [2.269]	0.981 [2.477] [2.057]	1.666 [2.528] [2.075]	2.976 [3.033] [1.950]	3.456 [2.839] [1.635]	0.452 [2.792] [2.378]	1.033 [2.461] [2.147]	1.825 [2.429] [1.921]	3.106 [2.533] [1.648]	3.457 [2.463] [1.822]
PCA:	0.481 [1.806] [1.532]	1.076 [1.629] [1.307]	1.904 [1.690] [1.026]	3.498 [1.432] [-0.468]	3.990 [1.057] [-0.608]	0.447 [2.850] [2.452]	1.016 [2.599] [2.347]	1.778 [2.537] [2.250]	2.997 [2.616] [2.244]	3.487 [2.351] [2.056]
PLS:	0.485 [1.904] [1.548]	1.023 [1.953] [1.714]	1.692 [2.042] [1.853]	2.904 [2.182] [1.994]	3.486 [2.039] [1.914]	0.479 [2.408] [2.106]	1.071 [2.429] [2.159]	1.833 [2.468] [2.191]	3.044 [2.385] [2.144]	3.485 [2.195] [2.117]
S [10]	0.540	1.243	2.123	3.401	3.828	0.540	1.243	2.123	3.401	3.828
# Signif. Mod.	**20**	**20**	**13**	**11**	**9**	**23**	**25**	**22**	**17**	**14**
# C&W Signif.	**29**	**26**	**26**	**23**	**13**	**29**	**26**	**26**	**23**	**15**
# Total Mod.	**30**	**30**	**30**	**30**	**30**	**30**	**30**	**30**	**30**	**30**
Best FS	**FS [4] (SA)**	**FS [7] (PCA)**	**FS [7] (PCA)**	**FS [4] (PCA)**	**FS [5] (PCA)**	**FS [7] (SA)**	**FS [7] (SA)**	**FS [7] (SA)**	**FS [5] (SA)**	**FS [7] (PCA)**
RMSPE	0.351	0.870	1.496	2.521	2.560	**0.351**	**0.832**	**1.483**	2.507	2.576
Best Benchmark	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**	**S [7]**
RMSPE	0.372	0.892	1.555	2.558	2.569	0.372	0.892	1.555	2.558	2.569

Note:
We show three figures on each cell of this table. These figures correspond to the Clark and West (2007) core and t-statistic and the t-statistic of the Giacomini and White (2006) test. Shaded cells indicate statistical significance at the 10% significance value. For instance, this table displays three figures in the upper left corner. All these figures are computed with one-step ahead forecast errors (h=1) coming from the FASARIMA 1 model (FS1). The first figure, 0.442, represents the core statistic of the Clark and West (2007) test. The second figure, [3.607], represents the approximately normal t-statistic of the Clark and West (2007) test. Finally, the third figure, [2.560], represents the asymptotically normal t-statistic of the Giacomini and White (2006) test. Both t-statistics are calculated using HAC estimation according to Newey and West (1987).

#. Signif. Mod. indicates the total number of significant figures on both tests, meanwhile, # C&W Signif. indicates the number of tests that reject the null according to the Clark and West test. In the last rows of the table we identify the FASARIMA model with the best forecasting performance. We show its corresponding RMSPE and the type of factor generating the best performance. We also report the best performing univariate benchmark with its corresponding RMSPE. Shaded cells in the last rows indicate that the Giacomini and White (2006) test rejects the null hypothesis favoring the FASARIMA models at least at the 10% significance level.
Source: Authors' elaboration

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