How informative are in-sample information criteria to forecasting? the case of Chilean GDP

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How Informative are In-Sample Information Criteria to Forecasting? The Case of Chilean GDP*

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Abstract

There is no standard economic forecasting procedure that systematically outperforms the others at all horizons and with any dataset. A common way to proceed, in many contexts, is to choose the best model within a family based on a fitting criteria, and then forecast. I compare the out-of-sample performance of a large number of autoregressive integrated moving average (ARIMA) models with some variations, chosen by three commonly used information criteria for model building: Akaike, Schwarz, and Hannan-Quinn. I perform this exercise to identify how to achieve the smallest root mean squared forecast error with models based on information criteria. I use the Chilean GDP dataset, estimating with a rolling window sample to generate one- to four-step ahead forecasts. Also, I examine the role of seasonal adjustment and the Easter effect on out-of-sample performance. After the estimation of more than 20 million models, the results show that Akaike and Schwarz are better criteria for forecasting purposes where the traditional ARMA specification is preferred. Accounting for the Easter effect improves the forecast accuracy only with seasonally adjusted data, and second-order stationarity is best.

Keywords: data mining, forecasting, ARIMA, seasonal adjustment, Easter-effect.

JEL-codes: C13, C22, C52, C53.

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1 Introduction

An accurate forecast is a key element for successful economic decision-making, but there is no standard procedure for selecting a model that systematically beats the others at all horizons and with any dataset. A common way to proceed is to choose the best specification within a family of models based on a fitting criterion, and then to generate a forecast. In this paper, I compare the out-of-sample performance of a large number of autoregressive integrated moving average models (ARIMA) chosen by three commonly used information criteria for model building: Akaike, Bayesian or Schwarz, and Hannan-Quinn[1] (henceforth AIC, BIC, and HQ), with a publicly available Chilean GDP dataset without revisions[2], estimated with a rolling window sample for 1- to 4-step-ahead forecasts. I also examine the role of seasonal adjustment and the Easter effect on out-of-sample performance, which becomes a pseudo-real-time exercise whose results are not comparable across all kinds of series (Ghysels, Osborn, and Rodrigues, 2006). The forecast evaluation is based on the root mean squared forecast error (RMSFE) and considers different aggregation blocks. I perform this exercise to determine which information criterion leads the forecaster to select the most accurate model.

The goals of this paper are: (i) to investigate the use of the traditional Box-Jenkins[3] approach to find an adequate out-of-sample benchmark for sectorial studies, going beyond the typical naive model; (ii) to provide an educated opinion on the use of three popular information criteria for forecasting in the Chilean economy; (iii) to investigate the accuracy achieved by using seasonally-adjusted data and considering the impact of the Easter effect on RMSFE as a parallel exercise; and (iv) to provide a systematic data snooping analysis to reveal what the dataset can tell us about the future, and to evaluate the informational gains from incorporating higher frequency variables in the model building process.

The results obtained with this exercise should be read with caution, given that the forecasts may come from models that explain more than what actually is explained by the data generating processes, known as overfitting. An overfitted model may have poor predictive performance, as it can exaggerate minor fluctuations in the data. In the context of this paper, the only mechanism to prevent overfitting is the penalty term imposed by each information criterion to the number of regressors included in the model. To identify which strategy offers the best accuracy in a statistical sense –and not by pure luck– it is necessary to perform a reality check, as developed in White (2000), Hansen (2005), and in the spirit of Pincheira (2011). Instead, this work tries to give clues on how to do so in a reduced and easy-to-handle context.

As pointed out by Granger and Jeon (2004), most results on comparing the performance between information criteria are theoretical, and the empirical evidence with

[1] See Akaike (1974), Schwarz (1978), and Hannan and Quinn (1979) for details.

[2] That is, not in real-time.

[3] See Box and Jenkins (1970).

actual data on the relative forecast accuracy from using each information criterion has not been thoroughly examined. Granger and Jeon (2001), by comparing the number of regressors chosen according to each information criterion, find that the AIC tends to select more dynamic models than that found using the BIC. Further, Clark (2004) proves that the number of (auto)regressors of a model is inversely related to out-of-sample forecast capacity, highlighting the cost of overfitting. This leads us to expect BIC to beat AIC in out-of-sample exercises. Moreover, Granger and Jeon (2004) find that an equally-weighted combination between the forecasts delivered by each information criterion increases efficiency. It is intuitive to think of HQ as a combination of the AIC and BIC by including a penalization of the number of regressors as well the asymptotic, suggesting that it may be worth learning about its out-of-sample model-based features. Notwithstanding, and besides some theoretical findings, I treat the matter of which information criterion outperforms the others as an empirical question, while being dependant on the characteristics of the dataset at hand to some extent. For example, in the case of Chilean inflation, Cobb (2009) uses multivariate time-series models based on AIC and BIC, finding that AIC consistently gives more predictive power. Using the proposed Extended SARIMA models, Pincheira and García (2010) also point out that AIC gives better predictive results than those chosen with BIC.

This paper also relates to seasonal adjustment and treatments of the Easter effect. I replicate the exercise of choosing the best ARMA model to generate multi-horizon forecasts in the same setting, considering data that has been seasonally adjusted using: (i) the X12-ARIMA methodology[4], and (ii) explicit regressors (Seasonal ARMA models, SARMA). As pointed out by Granger (1979), since seasonality can contribute substantially to the variance of a series while being economically unimportant, its absence helps to build more parsimonious models with a better fit[5]. More recently, Capistrán, Constandse, and Ramos-Francia (2010) estimate the portion of the Mexican CPI components due to seasonality, finding that it can account for almost 80% of the observed variation. Bell and Sotiris (2010) also show that certain fundamental choices about seasonal adjustment affect subsequent forecasts by improving their accuracy. I study the impact of the Easter effect –a special feature of seasonal components– on RMSFE in two ways: (i) including the regressors proposed by Bell and Hillmer (1983) in an ARMA environment, and (ii) isolating the seasonal adjustment process prior to modeling, by first including and later excluding the Easter effect using X12-ARIMA. The fundamental reason to make a statement about the out-of-sample impact of the Easter effect, particularly in the Chilean GDP series, lies in the findings of Cobb and Medel (2010) that its exclusion can generate seasonally-adjusted series with very different dynamics from those that include it, and because it is information known with high confidence several quarters after its realization. Both elements are subjects of interest to an out-of-sample evaluation, and also make the results uncomparable between the different kinds of data.

[4] The version of X12-ARIMA used in this paper is 0.2.7. A detailed description of the program can be found in Findley *et al.* (1998) and US Census Bureau (2007).

[5] A result shared by Bell (1995).

After the estimation of more than 20 million models, the results show the following. On average, with actual series, the information criteria that show lower RMSFE across all horizons are the AIC and BIC. While HQ forecasts better 1-step ahead, BIC does so at 2- and 3-steps ahead, and AIC at 4-steps ahead. In the case of seasonally-adjusted data, BIC shows better performance 1-step ahead, while AIC is the best at the remaining horizons.

In the case of model specification, the best results are obtained with ARMA and SARMA models, despite a tie at the 1-step ahead horizon between ARMA and ARMAX. The traditional ARMA specification outperforms at 1-, 2-, and 4-steps ahead, while SARMA does so in the remaining cases. This proves that the Easter effect does not help to improve forecasting with original series, a result contrary to that found with seasonally-adjusted data. Working with seasonally-adjusted series, the best results for all horizons are obtained with the ARMA specification that explicitly accounts for the Easter effect in X12-ARIMA.

Regarding the order of differencing, an overwhelming result is found in favor of second-order differencing with actual series: for all horizons the second differentiation outperforms by at least 50%. With seasonally-adjusted data there is mixed evidence. While the third order is best at 1- and 3-steps ahead, the second order is best for 2-steps ahead, and the first for 4-steps ahead.

There is a huge literature related to issues raised in this paper, especially on ARMA (unstructured) modeling[6], conjunctural forecasting (short-term and multi-horizon), seasonal adjustment, Easter-effect treatment, and information criteria for model building. Notwithstanding, this work follows closely in the spirit of Granger and Jeon (2004) by trying to reveal the empirical out-of-sample performance of in-sample information criteria using actual data, and doing so to determine if the behavior is slightly different. Stock and Watson (2007) also study the performance of many forecasting techniques with 215 macro series from the United States, including ARMA models chosen with information criteria and comparing those with nonlinear models. The results are mixed, but seasonality is found to play a role in favor of nonlinear models, and there are mixed results between AIC and BIC depending on the type of series employed.

For the case of Chile, no similar systematic analysis exists on the relative efficiency of information criteria using the same dataset. A related work is Medel and Urrutia (2010), which evaluates the forecasting procedure contained in the X12-ARIMA, but with a previous vintage of Chilean GDP data and using another criterion (Ljung-Box Q-statistic). This automatic procedure has the advantage that it filters the series of outliers and the Easter effect, reducing the variance of actual series. In this work I also try this procedure to model the seasonally-adjusted data, but this filtering makes the results uncomparable.

[6] A recent and complete survey on ARMA modeling and its variants is provided by Holan, Lund, and Davis (2010).

The paper is organized as follows. In section 2, I describe the Chilean GDP dataset, the transformations applied to achieve stationarity, and my treatment of seasonality and the Easter effect. In section 3, I explain the setting for model estimation, and in section 4, I analyze the results for each series by giving a recommendation of what specification, information criterion, and transformation is most accurate for each of the four horizons considered, and for the two kinds of data, based on the minimization of RMSFE. Finally, section 5 concludes.

2 Data

I use the Central Bank of Chile's Quarterly National Accounts (QNA) starting with GDP as the most aggregated, and with three levels of disaggregation on the demand and supply sides. The original series are in levels, denominated in millions of 2003 Chilean pesos. I use the first release of the QNA that includes 2010.IV, leaving a real-time analysis for further research[7]. The initial estimation sample covers 1986.I to 1995.IV (40 observations), and the size of the rolling window is kept fixed. The remaining sample for evaluation covers 1996.I to 2010.III (59 observations).

The series compound the Chilean GDP by demand and supply side. A scheme of demand-side aggregations of all series and the acronyms used in this paper are shown in Table 1, and of supply-side in Table 2.

Table 1: Chilean GDP by demand side

$gdp=id+ed=c+i+g+(x\text{-}m)=$ $(cn+cd)+(meq+cw+ci)+g+(xg+xs\text{-}mg\text{-}ms)$							
cn	Household consumption	*c*	Household consumption	*id*	Internal demand	*gdp*	Gross
	expenditure: nondurables		expenditure		*(c+i+g)*		domestic
cd	Household consumption		*(cn+cd)*	*ed*	External demand		product
	expenditure: durables	*i*	Investment		*(x-m)*		*(id+ed)*
meq	Machinery and equipment		*(meq+cw+ci)*				
cw	Construction and works	*g*	Government consumption				
ci	Changes in inventories (*)		expenditure *(g)*				
g	Government consumption	*x*	Exports				
	expenditure		*(xg+xs)*				
xg	Exports of goods	*m*	Imports (**)				
xs	Exports of services		*(mg+ms)*				
mg	Imports of goods (**)						
ms	Imports of services (**)						

(*) Not considered in analysis. (**) Imports are subtracted. Source: Central Bank of Chile.

[7]A framework for a real-time approach that can be used to this end is provided by Clements and Galvão (2010).

Table 2: Chilean GDP by supply side

gdp=gdp nr+gdp nnr+others=(egw+caf+min)+(com+man+con+agr+tra+fin+per+ood+pub)+(vat+cif-dut)					
gdp	Gross domestic product *(gdp nr+ gdp nnr+ others)*	*gdp nr*	GDP Natural resources *(egw+caf+min)*	*egw*	Electricity, gas and water
				caf	Capture fishery
		gdp nnr	GDP Non-natural resources *(com+man+con+ agr+tra+fin+ per+ood+pub)*	*min*	Mining
				com	Wholesale and retail trade, hotels and restaurants
				man	Manufacturing
		others	Other sectors *(-dut+vat+cif)*	*con*	Construction
				agr	Agriculture and forestry
				tra	Transportation and communications
				fin	Financial intermediation and business services
				per	Personal and social services
				ood	Owner-occupied dwellings
				pub	Public administration
				dut	Duties + taxes on goods and services (*)
				vat	Non-deductible VAT
				cif	Imports CIF

(*) DUT are subtracted. Source: Central Bank of Chile.

To achieve stationarity I consider the following five transformations[8]:

$$\begin{aligned}(i-iv) &: \Delta^d y_t = \Delta^d[\log(Y_t) - \log(Y_{t-1})],\ d=\{0,...,3\},\\ (v) &: y_t = (Y_t/Y_{t-4})\cdot 100 - 100,\end{aligned}$$

where Y_t is the variable in levels. Hereafter, these transformations are denominated *d1*, *d2*, *d3*, *d4* and *%*. All of these are stationary transformations of the series in levels.

Besides the use of actual data, the complete exercise is carried out with two kinds of seasonally-adjusted data: (i) with special regressors to control for seasonality (SARMA models), and (ii) with the X12-ARIMA procedure. In both cases the Easter effect is considered but of different forms. This effect relates to the fact that the composition of a month or quarter in terms on number of working days affects the dynamics of a series. Typical examples, in the Chilean case, are: retail in September (09/18 is Chilean independence day) and December (Christmas and New Year), manufacturing in the summer holiday month of February, and consumption in March (several one-time annual payments). It is considered "exogenous", as the X variables in ARMAX and SARMAX specifications[9] when the dependent variable is not seasonally adjusted. The

[8] In Table A1, in the appendix, I compute the typical statistics of all these transformations for all series (panel A: demand side, panel B: supply side).

[9] I use "exogenous" to mean that there is new information being used to model the dependent variable, instead of the case when it is considered *within* the seasonal adjustment with X12-ARIMA, in which case it is considered "endogenous".

X_t matrix contains a set of six series, defined as the number of working days within a quarter minus the number of Sundays within the same period, $Day_t = \{\#Day_t - \#Sunday_t\}$. Bell and Hillmer's (1983) regressors are thus:

$$X_t = \left[\begin{array}{ccc} Monday_t & ... & Saturday_t \end{array}\right].$$

The other case with seasonally-adjusted data consists of comparisons including and excluding the use of X12-ARIMA, such that I can isolate the impact of the Easter effect on forecast performance. As X12-ARIMA changes the autocorrelation structure of the series, the results when using this treatment are not comparable with those with regressors on actual series.

The treatment of the Easter effect by X12-ARIMA is as follows[10]. First, the program is an automatic procedure based on moving averages to seasonally adjust economic time series –that is, a separation of a series into a trend-cycle component (TC_t), a seasonal component (S_t), and an irregular component (I_t). This decomposition can be typically additive or multiplicative, depending on I_t (that it really be irregular) based on a battery of tests contained in the routine. So, supposing an additive decomposition, the series can be split as:

$$Y_t = TC_t + S_t + I_t,$$

where the seasonally-adjusted series corresponds to $Y_t - S_t$. Second, before the application of filters (moving averages) that identify the above mentioned components, X12-ARIMA applies a whitening based on a special module: regARIMA (regression with ARIMA noise), which automatically filters for the Easter-effect, leap years, level shifts, additive outliers, transitory changes, ramp, among other considerations[11]. By doing so, the whitening series added to the seasonally-adjusted series is $\widehat{Z}_t$, obtained from:

$$\begin{aligned} Y_t &= \sum_i \beta_{i|t} C_{i|t} + Z_t, \\ \widehat{Z}_t &= Y_t - \sum_i \widehat{\beta}_{i|t} C_{i|t}, \end{aligned}$$

where $C_{i|t}$ is the control i, and $\widehat{\beta}_{i|t}$ is the estimated coefficient associated to the control i. This implies that the predicted series is not the actual one, but rather an automatic filtered version. Third, the regressors applied by X12-ARIMA to control for the Easter effect consist of the same Bell and Hillmer regressors used in ARMAX and SARMAX specifications in this work. After the identification of all effects, the share excluded by filtering is added to the irregular component to preserve the equality $Y_t = TC_t + S_t + I_t$.

[10] A complete description can be found in US Census Bureau (2007).

[11] See Table 4.1, pp. 36-38, of US Census Bureau (2007) for formal definitions.

3 Setting up the estimations

3.1 Models

I estimate 6 families of models (with intercepts) for each of the five stationarity transformations mentioned above:

$$
\begin{aligned}
& & \text{Actual series:} \\
(i) & : & ARMAX(p,q),\ \ p,q=\{0,1,2,3,4\}, \\
(ii) & : & SARMAX(s,p,q),\ \ p,q=\{0,1,2,3,4\}, s=\{4\}, \\
(iii) & : & ARMA(p,q),\ \ p,q=\{0,1,2,3,4\}, \\
(iv) & : & SARMA(s,p,q),\ \ p,q=\{0,1,2,3,4\}, s=\{4\}, \\
& & \\
& & \text{Seasonally-adjusted series:} \\
(v) & : & ARMA(p,q),\ \ p,q=\{0,1,2,3,4\}, \textit{(X12-ARIMA sa with Easter effect)}, \\
(vi) & : & ARMA(p,q),\ \ p,q=\{0,1,2,3,4\}, \textit{(X12-ARIMA sa without Easter effect)}.
\end{aligned}
$$

I consider the fourth order for frequency considerations; hence, monthly cases are a bit more complicated to compute[12]. All the estimations were programmed using the *ARIMASel* add-in for Eviews 7.1. Each model is re-estimated as the rolling window is moved one observation ahead. Each family of models produces a total of 25 (without seasonal regressors) or 36 (with seasonal regressors) models by combining non-skipped AR(p), MA(q), SAR(s) and SMA(s) regressors with $(p,q) \subseteq \{0,1,2,3,4\}^2$ and $s=\{4\}$.

The three IC used are as follows:

$$
\begin{aligned}
\text{AIC} &: -2(\ell/T)+2(k/T), \\
\text{BIC} &: -2(\ell/T)+k\log(T)/T, \\
\text{HQ} &: -2(\ell/T)+2k\log(T)/T,
\end{aligned}
$$

where ℓ is the value of the log-likelihood function, with k parameters estimated using T observations. These expressions jointly imply that $BIC \leq AIC$ when $T \geq 8$, $BIC \leq HQ$ when $T \geq 2$, and $AIC \leq HQ$ when $T \geq 3$. In other words, it is expected for a reasonable sample size that $BIC \leq AIC \leq HQ$, because BIC puts a heavier penalty on additional parameters. From an empirical viewpoint, the resolution of this matter depends strictly on how the lag structure in the model fits the series, i.e. how systematic is the behavior of the series within a year across the years. I find some evidence in favor of the abovementioned inequalities with actual series, and also to a lesser extent, with seasonally-adjusted series.

Accounting for 5 transformations, 6 specifications, 34 variables, 4 horizons, 3 criteria, 28.6 averaged combinations of AR, MA, SAR, SMA regressors, 59 observations within

[12] Coincidentally, Granger and Jeon (2004) find that an AR(4) model re-estimated when a new monthly observation has been added to the sample, outperforms those chosen by AIC and BIC.

evaluation window, the number of estimated models raises:

$$5 \times 6 \times 34 \times 4 \times 3 \times 28.6 \times 59 = 20,653,776 \text{ models.}$$

The number of realized estimations is slightly lower because in a few cases the value of the log-likelihood function could not be computed.

3.2 Forecast evaluation

The evaluation of forecasts is based on comparisons of Root Mean Squared Forecast Error (RMSFE), defined as:

$$RMSFE_h = \left[\frac{1}{T} \sum_{t=1}^{T} (y_{t+h} - \widehat{y}_{t+h|t})^2 \right]^{\frac{1}{2}},$$

where $\widehat{y}_{t+h|t}$ is the forecast of y_{t+h} (with seasonal correction when appropriate), h-quarters ahead ($h = \{1, 2, 3, 4\}$), and T is the size of the evaluation sample (from 1996.I to 2010.III, 59 observations). Notwithstanding the transformations, the results are shown and the conclusions made with year-on-year variation of the series in levels. I do not consider any aggregation strategy nor combination of disaggregated data to obtain an aggregated forecast built from its components[13].

4 Results

This section provides a detailed analysis of the results for all horizons, series, specifications, transformations, and IC for every kind of data. The results obtained are fully computer-based, implying that extreme forecasts are not trimmed by the judgement of the forecaster[14]. Thus, the RMSFE results can be easily improved by avoiding such "crazy" forecasts by allowing for a "no change" forecast ($y_{t+h|t} = y_t$) given a threshold, as used by Stock and Watson (2007). I opt for not intervening to ensure a more fair comparison between the IC, and because it has relevant effects on accuracy as is highlighted by Mélard and Pasteels (2000).

There are two kinds of results: with and without seasonal adjustment, to allow a fair comparison of the RMSFE for the same dependent variable. For each variable, the following RMSFE is reported:

$$RMSFE_h^{\{IC,Model,Trans\}} = \min_{\{IC,Model,Trans\}} \left[\frac{1}{T} \sum_{i=1}^{T} (y_{t+h} - \widehat{y}_{t+h|t}^{\{IC,Model,Trans\}})^2 \right]^{\frac{1}{2}},$$

[13]Hyndman *et al.* (2011) provide a methodology of the so-called *hierarchical forecasts*, that is, to consider a particular structure of aggregate forecasts based on disaggregations chasing efficiency.

[14]See Goodwin, Önkal, and Lawrence (2011) for a formal treatment of the role of the forecaster's judgment in forecasting practice.

where:

$$
\begin{aligned}
IC &= \{AIC, BIC, HQ\}, \\
Model &= \{ARMAX, SARMAX, ARMA, SARMA\}, \text{ if data is not seasonally-adjusted, or} \\
Model &= \{ARMA^{E-e}, ARMA^{No}\}, \text{ if data includes a seasonal correction,}
\end{aligned}
$$

with $ARMA^c$ corresponding to:

$$
\begin{aligned}
ARMA^{E-e} &: \text{ seasonally-adjusted data with a treatment of the Easter-effect, and} \\
ARMA^{No} &: \text{ seasonally-adjusted data without accounting for the Easter-effect.}
\end{aligned}
$$

Finally, $Trans = \{d1, ..., d4, \%\}$ are the transformations for stationarity. The RMSFE ratio, defined as the lowest RMSFE obtained with seasonally adjusted data divided by the lowest RMSFE obtained with seasonally unadjusted data, is also reported.

As I said, these results should be read with caution given the issue of overfitting. An overfitted model may have poor predictive performance, as it can exaggerate minor fluctuations in the data. Given that, all the results identifying the best forecasting strategy, that are not statistically tested against one or several rivals may be obtained as a special case of the sample, in other words, by pure luck. A common way to face the misleading inference coming from data snooping exercises is by performing a reality check (White, 2000). Instead, the aim of this paper is to give a first look at what elements (i.e. specifications, transformations, data filtering, etc.) need to be present to carry out a less cumbersome reality check.

The results are shown in Tables 3 to 6. For each variable the lowest RMSFE, information criteria, model, and transformation that gives the most accurate forecasts are reported. For each horizon the results show the following:

- For 1-step ahead the results are shown in Table 3. The results show that the Easter effect plays a non-prominent role at this horizon for both kinds of adjusted data. In the case of actual series, the IC that work best are HQ and AIC for the demand side, HQ for the supply side, and HQ dominates over the entire horizon. The preferred specification is a simple ARMA model, and the most frequent transformation used is the second-order of differencing, for both the demand and supply sides. In the case of seasonally adjusted data, the ICs with better performance for the supply side are AIC and BIC, and for the demand side there is virtually a tie between the three IC. The preferred orders for differencing are the second and the third.

- For 2-steps ahead the results are shown in Table 4. When the forecasted series is the actual one, it is recommended to estimate an ARMA or SARMA model chosen according to the BIC, using the second difference of series in levels, for both the demand and supply sides. As in the 1-step ahead case, the Easter effect plays no role in improving forecast accuracy with actual series. For forecasts with seasonally-adjusted data, the recommendation is to use the series that includes the Easter effect modeled with an ARMA specification chosen by AIC, and for the unadjusted series, using the second order of differencing.

- For 3-steps ahead the results are shown in Table 5. For actual series, the results are similar to the previous case, such that it is recommended to model the actual series with a SARMA specification chosen with the BIC, using the second order of differencing. To forecast with seasonally-adjusted data, the recommendation is to use the series that includes the Easter effect modeled with an ARMA specification chosen by AIC, and using the third or the first order of differencing.

- For 4-steps ahead the results are shown in Table 6. For actual series, the results show that modeling with a traditional ARMA specification chosen by AIC, using the second order of differencing of the dependent variable yields the best forecast accuracy. To forecast with seasonally-adjusted data, the recommendation is to use the series that includes the Easter effect modeled with an ARMA specification chosen by AIC, and using the first order of differencing.

Table 3: RMSFE results for demand and supply side (h=1)

	Not seasonally adjusted				Seasonally adjusted				RMSFE
	RMSFE	IC	Model	Transf	RMSFE	IC	Model	Transf	ratio
cn	2.08	BIC	ARMA	d2	1.16	HQ	ARMA^{No}	d3	0.56
cd	9.72	AIC	SARMA	d4	7.20	BIC	ARMA^{No}	d2	0.74
meq	13.70	HQ	ARMAX	d2	9.41	HQ	ARMA^{E-e}	d3	0.69
cw	5.81	AIC	SARMA	d2	4.25	AIC	ARMA^{E-e}	d3	0.73
g	1.84	AIC	ARMA	d2	0.48	BIC	ARMA^{No}	d3	0.26
xg	5.60	HQ	ARMAX	d3	3.87	BIC	ARMA^{No}	d1	0.69
xs	10.86	HQ	ARMAX	d1	6.72	BIC	ARMA^{E-e}	d2	0.62
(mg)	7.72	BIC	ARMAX	d2	6.22	HQ	ARMA^{E-e}	d2	0.81
(ms)	6.41	BIC	ARMA	d1	4.51	BIC	ARMA^{E-e}	d1	0.70
c	2.46	HQ	ARMA	d2	1.62	HQ	ARMA^{No}	d2	0.66
i	6.79	AIC	SARMAX	d3	5.01	HQ	ARMA^{E-e}	d3	0.74
x	6.19	AIC	SARMA	d2	4.34	AIC	ARMA^{No}	d1	0.70
(m)	6.14	AIC	SARMAX	d2	4.90	AIC	ARMA^{E-e}	d2	0.80
id	2.97	BIC	SARMAX	d2	2.34	AIC	ARMA^{E-e}	d2	0.79
ed	2.12	HQ	ARMA	d2	1.25	BIC	ARMA^{No}	d3	0.59
gdp	2.26	HQ	ARMAX	d3	1.49	AIC	ARMA^{E-e}	d2	0.66
egw	6.52	HQ	ARMA	d3	6.70	BIC	ARMA^{No}	d2	1.03
min	3.76	BIC	SARMA	d2	2.64	AIC	ARMA^{No}	d3	0.70
caf	11.76	BIC	SARMA	d2	6.07	BIC	ARMA^{E-e}	d1	0.52
agr	5.86	HQ	ARMA	d2	1.78	HQ	ARMA^{E-e}	d3	0.30
man	2.76	BIC	ARMAX	d2	1.77	HQ	ARMA^{E-e}	d2	0.64
com	4.19	HQ	ARMAX	d2	2.18	AIC	ARMA^{No}	d4	0.52
con	4.88	AIC	SARMA	d3	4.51	AIC	ARMA^{No}	d3	0.92
tra	1.85	BIC	ARMA	d2	1.48	BIC	ARMA^{No}	d2	0.80
fin	2.33	AIC	SARMA	d3	1.73	AIC	ARMA^{E-e}	d2	0.74
per	2.06	HQ	ARMA	d2	0.71	BIC	ARMA^{E-e}	d1	0.35
ood	0.08	BIC	ARMAX	d3	0.06	AIC	ARMA^{No}	d3	0.70
pub	0.29	HQ	SARMA	d3	0.18	BIC	ARMA^{No}	d1	0.60
(dut)	2.35	HQ	ARMAX	d3	1.76	AIC	ARMA^{E-e}	d2	0.75
vat	2.29	AIC	SARMA	d2	1.40	HQ	ARMA^{No}	d3	0.61
cif	8.58	AIC	ARMA	d1	6.92	BIC	ARMA^{E-e}	d3	0.81
$gdp\ nr$	2.91	HQ	ARMA	d1	2.29	AIC	ARMA^{E-e}	d2	0.79
$gdp\ nnr$	2.44	AIC	ARMAX	d1	1.71	BIC	ARMA^{No}	d3	0.70
$others$	2.50	HQ	ARMAX	d3	1.59	HQ	ARMA^{No}	d3	0.63

Source: Author's computations.

Table 4: RMSFE results for demand and supply side (h=2)

	Not seasonally adjusted				Seasonally adjusted				RMSFE
	RMSFE	IC	Model	Transf	RMSFE	IC	Model	Transf	ratio
cn	4.58	HQ	ARMA	d2	1.33	AIC	ARMA^{No}	d1	0.29
cd	77.14	HQ	SARMA	d4	32.97	HQ	ARMA^{E-e}	d2	0.43
meq	157.13	HQ	ARMAX	d2	91.89	BIC	ARMA^{E-e}	d3	0.58
cw	43.87	BIC	SARMA	d2	20.19	AIC	ARMA^{E-e}	d1	0.46
g	2.29	BIC	ARMA	d2	0.23	BIC	ARMA^{No}	d3	0.10
xg	28.03	AIC	SARMA	d2	14.11	HQ	ARMA^{No}	d1	0.50
xs	133.61	BIC	ARMA	d3	68.89	BIC	ARMA^{E-e}	d2	0.52
(mg)	90.59	BIC	ARMAX	d1	40.76	HQ	ARMA^{E-e}	d2	0.45
(ms)	43.39	BIC	SARMA	d3	12.81	AIC	ARMA^{E-e}	d2	0.29
c	5.53	AIC	ARMA	d3	2.56	AIC	ARMA^{E-e}	d1	0.46
i	36.98	AIC	SARMAX	d3	26.70	HQ	ARMA^{E-e}	d2	0.72
x	22.95	AIC	SARMA	d2	16.24	BIC	ARMA^{No}	d1	0.71
(m)	54.80	BIC	SARMAX	d2	23.30	AIC	ARMA^{E-e}	d3	0.43
id	12.32	BIC	SARMAX	d2	5.30	AIC	ARMA^{E-e}	d2	0.43
ed	3.54	BIC	SARMA	d3	1.52	HQ	ARMA^{No}	d3	0.43
gdp	4.39	AIC	SARMAX	d2	2.32	BIC	ARMA^{No}	d2	0.53
egw	44.84	AIC	ARMA	d2	36.83	BIC	ARMA^{No}	d1	0.82
min	17.19	BIC	SARMA	d2	7.09	AIC	ARMA^{No}	d3	0.41
caf	150.37	BIC	SARMA	d2	35.45	BIC	ARMA^{E-e}	d1	0.24
agr	33.94	BIC	ARMA	d2	4.27	HQ	ARMA^{E-e}	d2	0.13
man	11.71	BIC	ARMA	d1	4.19	HQ	ARMA^{E-e}	d2	0.36
com	14.58	BIC	ARMAX	d2	5.32	BIC	ARMA^{E-e}	d2	0.37
con	32.05	AIC	SARMA	d2	26.36	HQ	ARMA^{No}	d2	0.82
tra	3.60	BIC	ARMA	d3	2.33	HQ	ARMA^{No}	d2	0.65
fin	5.06	AIC	SARMA	d2	2.99	AIC	ARMA^{E-e}	d2	0.59
per	2.20	HQ	ARMA	d3	0.52	BIC	ARMA^{E-e}	d1	0.24
ood	0.01	BIC	ARMAX	d3	0.00	HQ	ARMA^{No}	d3	0.56
pub	0.09	BIC	SARMA	d3	0.04	AIC	ARMA^{E-e}	d1	0.43
(dut)	6.32	HQ	ARMAX	d3	3.23	AIC	ARMA^{E-e}	d2	0.51
vat	4.76	AIC	ARMA	d1	2.15	AIC	ARMA^{No}	d3	0.45
cif	55.93	AIC	ARMAX	d2	50.11	BIC	ARMA^{E-e}	d1	0.90
$gdp\ nr$	8.23	BIC	ARMA	d1	6.67	AIC	ARMA^{E-e}	d2	0.81
$gdp\ nnr$	5.88	AIC	ARMAX	d1	2.92	AIC	ARMA^{No}	d1	0.50
$others$	5.43	AIC	ARMA	d1	2.29	AIC	ARMA^{No}	d3	0.42

Source: Author's computations.

Table 5: RMSFE results for demand and supply side (h=3)

	Not seasonally adjusted				Seasonally adjusted				RMSFE
	RMSFE	IC	Model	Transf.	RMSFE	IC	Model	Transf.	ratio
cn	5.32	AIC	ARMA	d3	1.31	AIC	ARMA^{No}	d3	0.25
cd	137.05	HQ	ARMAX	d2	31.01	AIC	ARMA^{E-e}	d4	0.23
meq	137.75	AIC	ARMAX	d2	91.87	BIC	ARMA^{E-e}	d3	0.67
cw	37.66	BIC	SARMA	d2	22.45	AIC	ARMA^{E-e}	d2	0.60
g	1.74	BIC	SARMA	d2	0.46	BIC	ARMA^{E-e}	d3	0.26
xg	31.07	AIC	SARMA	d1	13.70	HQ	ARMA^{No}	d1	0.44
xs	83.32	AIC	ARMA	d2	28.94	HQ	ARMA^{E-e}	d2	0.35
(mg)	66.61	BIC	SARMA	d3	35.75	AIC	ARMA^{E-e}	d2	0.54
(ms)	36.38	AIC	ARMAX	d1	13.08	AIC	ARMA^{E-e}	d2	0.36
c	4.15	HQ	SARMA	d2	1.70	AIC	ARMA^{E-e}	d1	0.41
i	50.20	AIC	ARMA	d2	22.65	AIC	ARMA^{E-e}	d1	0.45
x	25.48	AIC	SARMA	d2	12.57	BIC	ARMA^{No}	d1	0.49
(m)	58.93	BIC	ARMAX	d4	27.55	BIC	ARMA^{E-e}	d2	0.47
id	14.29	BIC	SARMAX	d2	6.21	HQ	ARMA^{E-e}	d2	0.43
ed	3.91	BIC	SARMA	d3	1.25	HQ	ARMA^{No}	d1	0.32
gdp	4.10	BIC	ARMAX	d3	2.70	AIC	ARMA^{No}	d3	0.66
egw	50.77	AIC	ARMA	d2	35.39	AIC	ARMA^{No}	d1	0.70
min	18.54	BIC	SARMA	d2	8.64	BIC	ARMA^{No}	d3	0.47
caf	140.02	BIC	SARMA	d2	45.74	BIC	ARMA^{E-e}	d1	0.33
agr	31.44	HQ	ARMA	d2	4.92	AIC	ARMA^{E-e}	d3	0.16
man	6.59	AIC	ARMAX	d2	3.75	HQ	ARMA^{E-e}	d21	0.57
com	15.34	BIC	ARMA	d2	4.64	BIC	ARMA^{No}	d2	0.30
con	30.74	BIC	SARMA	d2	29.84	HQ	ARMA^{No}	d2	0.97
tra	4.62	BIC	ARMA	d3	2.17	HQ	ARMA^{No}	d1	0.48
fin	5.14	AIC	ARMA	d2	2.71	BIC	ARMA^{E-e}	d1	0.53
per	3.29	BIC	ARMA	d3	0.60	BIC	ARMA^{E-e}	d3	0.18
ood	0.01	BIC	ARMAX	d2	0.00	AIC	ARMA^{No}	d1	0.45
pub	0.08	AIC	SARMA	d3	0.03	AIC	ARMA^{E-e}	d3	0.42
(dut)	5.71	HQ	ARMAX	d2	3.65	AIC	ARMA^{E-e}	d3	0.64
vat	3.98	AIC	SARMA	d2	2.30	BIC	ARMA^{No}	d3	0.58
cif	61.09	BIC	ARMAX	d2	50.75	BIC	ARMA^{E-e}	d3	0.83
$gdp\,nr$	5.87	BIC	ARMA	d1	6.12	AIC	ARMA^{No}	d2	1.04
$gdp\,nnr$	5.33	BIC	SARMAX	d1	2.82	BIC	ARMA^{No}	d3	0.53
$others$	5.00	AIC	ARMA	d1	2.10	BIC	ARMA^{No}	d3	0.42

Source: Author's computations.

Table 6: RMSFE results for demand and supply side (h=4)

	Not seasonally adjusted				Seasonally adjusted				RMSFE
	RMSFE	IC	Model	Transf.	RMSFE	IC	Model	Transf.	ratio
cn	5.38	AIC	ARMA	d2	1.18	AIC	ARMA^{No}	d3	0.22
cd	90.94	AIC	SARMA	d4	29.04	HQ	ARMA^{E-e}	d2	0.32
meq	148.95	AIC	ARMAX	d2	87.47	HQ	ARMA^{E-e}	d3	0.59
cw	46.29	BIC	ARMA	d2	23.04	AIC	ARMA^{E-e}	d2	0.50
g	2.08	HQ	ARMA	d3	0.41	BIC	ARMA^{No}	d3	0.20
xg	28.87	HQ	ARMA	d1	10.90	BIC	ARMA^{No}	d1	0.38
xs	93.92	HQ	ARMA	d2	34.90	HQ	ARMA^{E-e}	d2	0.37
(mg)	71.09	HQ	ARMAX	d3	40.12	AIC	ARMA^{E-e}	d2	0.56
(ms)	38.01	BIC	ARMA	d1	17.74	AIC	ARMA^{E-e}	d2	0.47
c	3.57	AIC	SARMA	d2	2.37	BIC	ARMA^{E-e}	d1	0.66
i	42.20	AIC	ARMAX	d2	19.27	AIC	ARMA^{E-e}	d3	0.46
x	26.67	AIC	SARMA	d2	14.14	HQ	ARMA^{E-e}	d2	0.53
(m)	41.70	BIC	ARMAX	d1	23.90	BIC	ARMA^{E-e}	d1	0.57
id	16.72	HQ	ARMAX	d3	5.92	HQ	ARMA^{E-e}	d3	0.35
ed	4.51	AIC	ARMA	d2	1.52	HQ	ARMA^{No}	d2	0.34
gdp	3.57	AIC	ARMAX	d3	2.37	HQ	ARMA^{E-e}	d3	0.66
egw	46.98	BIC	ARMA	d3	44.38	AIC	ARMA^{E-e}	d1	0.94
min	14.37	AIC	ARMA	d2	8.03	AIC	ARMA^{No}	d3	0.56
caf	114.49	BIC	SARMA	d2	47.52	BIC	ARMA^{E-e}	d1	0.42
agr	37.53	HQ	SARMA	d2	9.16	AIC	ARMA^{No}	d2	0.24
man	8.24	AIC	ARMAX	d2	3.46	AIC	ARMA^{E-e}	d3	0.42
com	12.41	HQ	ARMAX	d3	5.01	BIC	ARMA^{E-e}	d1	0.40
con	40.04	HQ	ARMA	d2	26.36	AIC	ARMA^{E-e}	d1	0.66
tra	3.85	BIC	ARMA	d3	2.09	AIC	ARMA^{No}	d1	0.54
fin	5.26	BIC	SARMA	d2	3.86	HQ	ARMA^{No}	d1	0.73
per	2.28	BIC	ARMA	d3	0.61	BIC	ARMA^{E-e}	d1	0.27
ood	0.00	HQ	ARMAX	d3	0.00	BIC	ARMA^{No}	d3	0.69
pub	0.09	BIC	SARMA	d2	0.03	AIC	ARMA^{E-e}	d1	0.32
(dut)	5.56	AIC	ARMAX	d3	3.61	HQ	ARMA^{E-e}	d2	0.65
vat	4.62	HQ	ARMA	d1	1.82	BIC	ARMA^{No}	d1	0.39
cif	54.92	HQ	ARMAX	d2	45.78	BIC	ARMA^{E-e}	d1	0.83
$gdp\ nr$	7.08	BIC	ARMA	d3	4.25	BIC	ARMA^{No}	d3	0.60
$gdp\ nnr$	5.56	AIC	SARMA	d2	2.41	HQ	ARMA^{E-e}	d3	0.43
$others$	5.35	AIC	ARMA	d1	2.40	AIC	ARMA^{No}	d1	0.45

Source: Author's computations.

Table 7 presents a summary of findings for all IC, models, and transformations, series and horizons. It states the shares of cases in which an IC gives the most accurate forecasts for both kinds of series. For seasonally unadjusted series the best model specification for forecasting purposes is a traditional ARMA estimation. The Easter effect plays no role in improving the forecast performance. The overall order of differencing that fits better is the second. When the forecasted series is seasonally adjusted, the results show that the ARMA model chosen with AIC gives better performance, closely followed by BIC, and finally HQ. It is preferrable that the dependent variable includes the Easter-effect treatment provided by X12-ARIMA. There is weak evidence in favor of using the second order of differencing, while the first and third also perform well. The year-on-year variation of series in levels never gives the best forecasting results in either kind of data.

Table 7: Summary of findings

	h=1	*h=2*	*h=3*	*h=4*	*All*	*h=1*	*h=2*	*h=3*	*h=4*	*All*
	NSA	NSA	NSA	NSA	NSA	SA	SA	SA	SA	SA
					IC (%)					
AIC	32%	35%	38%	38%	36%	35%	42%	41%	38%	39%
BIC	27%	50%	50%	30%	39%	38%	29%	38%	32%	35%
HQ	41%	15%	12%	32%	25%	27%	29%	21%	30%	26%
					Model (%)					
ARMAX	32%	21%	27%	32%	29%	-	-	-	-	-
SARMAX	9%	12%	6%	0%	7%	-	-	-	-	-
ARMA	32%	35%	32%	44%	35%	-	-	-	-	-
SARMA	27%	32%	35%	24%	29%	-	-	-	-	-
ARMA^{E-e}	-	-	-	-	-	50%	59%	56%	62%	57%
ARMA^{No}	-	-	-	-	-	50%	41%	44%	38%	43%
					Transformation (%)					
d1	15%	18%	15%	15%	16%	18%	32%	32%	41%	31%
d2	50%	50%	59%	50%	52%	38%	44%	29%	27%	35%
d3	32%	29%	23%	32%	29%	41%	24%	35%	32%	33%
d4	3%	3%	3%	3%	3%	3%	0%	3%	0%	1%
%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

NSA: Not seasonally adjusted. SA: Seasonally adjusted.

Source: Author's computations.

A bird's eye view reveals that the strategy analyzed in this work does not encounter a single optimal forecast strategy across horizons, in the sense of Patton and Timmermann (2010). Their main claim is that the RMSFE must increase or at least remain constant as the forecast horizon increases. As a counterpart, the squared forecast must decline or remain constant for each additional forecast. The covariance between these two series is supposed to have an expected value equal to zero. If that is what occurs, then that forecast strategy is optimal under a quadratic loss function across horizons. If it is not the case, it is possible to improve quality by using the same information set used to forecast. A coarse check can be made by observing the results of which report RMSFE (Tables 3-6). Only in three cases of actual and four with seasonal-adjusted data can this optimality be observed without a formal test: for unadjusted series of exports (x), internal demand (id), and household consumption expenditure (c), and for adjusted series of construction and works (cw), imports of services (ms), capture fishery (caf), and agriculture and forestry (agr).

5 Concluding remarks

The main aim of this paper is to identify which of three commonly used IC has the highest predictive power to forecast Chilean GDP and its components. Over 20 million ARMA models were estimated using stationary transformations of the original series. Then, there were computer-based non-trimmed projections from 1- to 4-steps ahead using a rolling window estimation scheme for a sample of 59 observations. I also investigate the effect of seasonality and the impact of the Easter effect on the RMSFE.

On average, the ICs that show the lowest RMSFE across all horizons are the BIC and AIC. While HQ forecasts better for the original series at a horizon of 1-step ahead, BIC does so better at 2- and 3-steps ahead, and AIC at 4-steps ahead. With seasonally-adjusted data, BIC shows better performance 1-step ahead, and AIC in the remaining horizons.

For model specification, the best results are obtained with ARMA and SARMA models. A traditional ARMA specification outperforms 1-, 2- and 4-steps ahead, while SARMA does so in the remaining case. This implies that the Easter effect does not help to improve forecasting with original series. For seasonally-adjusted series, the best results for all horizons are obtained with ARMA specifications that include the Easter effect.

Regarding the order of differencing, an overwhelming result is found in favor of second-order differencing with actual series: for all horizons the second difference is better 50% or more of the times. With seasonally-adjusted data there is mixed evidence. While the third order is the best 1- and 3-steps ahead, the second order is for 2-steps ahead, and the first for 4-steps ahead.

These results must be read with caution, given the exposure of the forecasting process to the problem of overfitting that may arise. This work moves in that direction, by identifying key elements that a reality check should evaluate.

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Appendix

A Typical statistics of series

Table 1A: Typical statistics of demand side series, full sample

	Mean (Standard deviation)					Maximum (Minimum)				
	d1	*d2*	*d3*	*d4*	%	*d1*	*d2*	*d3*	*d4*	%
cn	0.014 (0.054)	0.000 (0.100)	0.001 (0.194)	−0.003 (0.381)	0.058 (0.029)	0.135 (-0.084)	0.172 (-0.203)	0.331 (-0.358)	0.670 (-0.634)	0.157 (-0.018)
cd	0.033 (0.152)	−0.006 (0.247)	0.003 (0.449)	−0.021 (0.845)	0.139 (0.209)	0.582 (-0.341)	0.637 (-0.695)	1.019 (-1.002)	1.267 (-1.909)	0.769 (-0.361)
meq	0.031 (0.114)	−0.002 (0.175)	−0.005 (0.313)	−0.009 (0.584)	0.147 (0.207)	0.310 (-0.384)	0.382 (-0.423)	0.714 (-0.746)	1.215 (-1.199)	0.645 (-0.319)
cw	0.014 (0.080)	0.000 (0.120)	−0.002 (0.199)	−0.005 (0.349)	0.062 (0.096)	0.203 (-0.176)	0.263 (-0.235)	0.342 (-0.438)	0.702 (-0.617)	0.327 (-0.218)
g	0.011 (0.117)	−0.001 (0.197)	−0.001 (0.350)	−0.007 (0.652)	0.041 (0.023)	0.199 (-0.182)	0.357 (-0.184)	0.517 (-0.536)	0.663 (-1.046)	0.086 (-0.039)
xg	0.017 (0.102)	−0.002 (0.154)	0.004 (0.241)	−0.004 (0.392)	0.073 (0.071)	0.235 (-0.213)	0.364 (-0.363)	0.639 (-0.613)	1.076 (-0.981)	0.246 (-0.065)
xs	0.016 (0.383)	0.014 (0.580)	−0.011 (0.954)	0.003 (1.686)	0.130 (0.291)	1.290 (-1.236)	2.287 (-2.242)	2.643 (-3.177)	5.206 (-5.270)	1.693 (-0.462)
(mg)	0.031 (0.074)	−0.001 (0.100)	−0.001 (0.164)	−0.003 (0.285)	0.128 (0.136)	0.195 (-0.260)	0.300 (-0.215)	0.465 (-0.287)	0.658 (-0.743)	0.413 (-0.224)
(ms)	0.020 (0.112)	−0.003 (0.176)	0.004 (0.302)	−0.004 (0.551)	0.077 (0.101)	0.380 (-0.226)	0.541 (-0.400)	0.762 (-0.941)	1.480 (-1.703)	0.473 (-0.279)
c	0.016 (0.058)	0.000 (0.109)	0.000 (0.210)	−0.004 (0.412)	0.063 (0.039)	0.138 (-0.093)	0.173 (-0.208)	0.344 (-0.369)	0.699 (-0.652)	0.181 (-0.051)
i	0.022 (0.071)	−0.001 (0.109)	−0.003 (0.198)	−0.007 (0.372)	0.098 (0.132)	0.219 (-0.235)	0.268 (-0.297)	0.485 (-0.553)	0.730 (-0.913)	0.368 (-0.256)
x	0.017 (0.099)	0.001 (0.146)	0.001 (0.227)	−0.002 (0.368)	0.077 (0.069)	0.261 (-0.203)	0.286 (-0.376)	0.552 (-0.533)	1.013 (-0.654)	0.271 (-0.072)
(m)	0.029 (0.069)	−0.002 (0.095)	0.001 (0.158)	−0.004 (0.281)	0.116 (0.118)	0.233 (-0.219)	0.255 (-0.188)	0.388 (-0.414)	0.549 (-0.802)	0.349 (-0.192)
id	0.018 (0.056)	−0.002 (0.098)	0.000 (0.185)	−0.005 (0.359)	0.069 (0.067)	0.159 (-0.118)	0.204 (-0.220)	0.357 (-0.418)	0.707 (-0.716)	0.212 (-0.100)
ed	0.015 (0.064)	−0.001 (0.122)	0.000 (0.240)	−0.005 (0.474)	0.059 (0.033)	0.117 (-0.099)	0.193 (-0.199)	0.370 (-0.346)	0.704 (-0.685)	0.157 (-0.039)
gdp	0.013 (0.040)	−0.001 (0.069)	0.000 (0.126)	−0.005 (0.238)	0.054 (0.037)	0.094 (-0.082)	0.164 (-0.127)	0.272 (-0.210)	0.396 (-0.482)	0.163 (-0.045)

Source: Author's computations.

Table 1B: Typical statistics of supply side series, full sample

	Mean (Standard deviation)					Maximum (Minimum)				
	d1	*d2*	*d3*	*d4*	%	*d1*	*d2*	*d3*	*d4*	%
egw	0.011 (0.070)	-0.001 (0.090)	0.002 (0.143)	-0.001 (0.247)	0.047 (0.141)	0.203 (-0.219)	0.246 (-0.215)	0.333 (-0.295)	0.564 (-0.618)	0.483 (-0.387)
min	0.010 (0.069)	0.000 (0.117)	-0.001 (0.215)	-0.004 (0.408)	0.043 (0.064)	0.155 (-0.144)	0.204 (-0.298)	0.468 (-0.433)	0.826 (-0.691)	0.181 (-0.086)
caf	0.010 (0.283)	-0.008 (0.434)	0.002 (0.707)	-0.011 (1.215)	0.065 (0.141)	0.661 (-0.524)	0.967 (-0.869)	1.567 (-1.724)	2.750 (-3.048)	0.458 (-0.374)
agr	0.002 (0.516)	-0.007 (0.729)	-0.003 (1.041)	-0.009 (1.509)	0.052 (0.048)	0.903 (-0.892)	1.070 (-1.076)	1.915 (-1.948)	2.511 (-2.307)	0.177 (-0.097)
man	0.010 (0.041)	-0.001 (0.066)	0.001 (0.118)	-0.003 (0.221)	0.039 (0.051)	0.116 (-0.130)	0.163 (-0.197)	0.356 (-0.282)	0.591 (-0.565)	0.187 (-0.122)
com	0.016 (0.083)	-0.001 (0.136)	0.001 (0.241)	-0.005 (0.445)	0.067 (0.060)	0.204 (-0.108)	0.293 (-0.232)	0.460 (-0.525)	0.811 (-0.985)	0.236 (-0.092)
con	0.013 (0.074)	0.000 (0.113)	-0.002 (0.190)	-0.005 (0.337)	0.056 (0.085)	0.178 (-0.149)	0.210 (-0.245)	0.347 (-0.456)	0.736 (-0.620)	0.304 (-0.190)
tra	0.020 (0.033)	0.000 (0.055)	0.000 (0.101)	-0.003 (0.190)	0.080 (0.044)	0.091 (-0.082)	0.165 (-0.130)	0.296 (-0.217)	0.460 (-0.512)	0.212 (-0.030)
fin	0.016 (0.044)	-0.001 (0.073)	0.001 (0.132)	-0.004 (0.248)	0.065 (0.045)	0.129 (-0.093)	0.136 (-0.197)	0.321 (-0.307)	0.628 (-0.480)	0.170 (-0.043)
per	0.012 (0.216)	-0.003 (0.370)	0.001 (0.673)	-0.013 (1.274)	0.036 (0.015)	0.357 (-0.361)	0.706 (-0.396)	1.102 (-1.036)	1.534 (-2.137)	0.071 (-0.017)
ood	0.006 (0.003)	0.000 (0.003)	0.000 (0.004)	0.000 (0.005)	0.026 (0.009)	0.012 (-0.013)	0.025 (-0.021)	0.026 (-0.022)	0.041 (-0.022)	0.040 (-0.006)
pub	0.004 (0.006)	0.000 (0.009)	0.002 (0.016)	0.000 (0.028)	0.018 (0.013)	0.019 (-0.026)	0.026 (-0.041)	0.067 (-0.068)	0.135 (0.105)	0.040 (-0.022)
(dut)	0.016 (0.041)	0.000 (0.058)	0.000 (0.088)	-0.001 (0.136)	0.065 (0.049)	0.107 (-0.096)	0.173 (-0.116)	0.289 (-0.193)	0.340 (-0.458)	0.186 (-0.046)
vat	0.012 (0.034)	-0.001 (0.058)	-0.002 (0.108)	-0.004 (0.204)	0.051 (0.034)	0.079 (-0.068)	0.117 (-0.110)	0.215 (-0.171)	0.330 (-0.372)	0.134 (-0.042)
cif	0.033 (0.086)	-0.004 (0.128)	0.000 (0.221)	-0.007 (0.402)	0.140 (0.151)	0.256 (-0.177)	0.318 (-0.360)	0.538 (-0.658)	1.055 (-1.196)	0.448 (-0.201)
$gdp\ nr$	0.010 (0.053)	-0.001 (0.086)	0.000 (0.153)	-0.001 (0.284)	0.043 (0.056)	0.196 (-0.096)	0.265 (-0.169)	0.341 (-0.428)	0.593 (-0.725)	0.218 (-0.087)
$gdp\ nnr$	0.013 (0.037)	-0.001 (0.064)	0.000 (0.119)	-0.004 (0.228)	0.052 (0.035)	0.080 (-0.070)	0.129 (-0.116)	0.222 (-0.196)	0.340 (-0.419)	0.142 (-0.045)
$others$	0.013 (0.034)	-0.001 (0.057)	0.000 (0.105)	-0.004 (0.199)	0.052 (0.034)	0.078 (-0.068)	0.112 (-0.110)	0.204 (-0.167)	0.316 (-0.357)	0.136 (-0.045)
gdp	0.013 (0.040)	-0.001 (0.069)	0.000 (0.126)	-0.005 (0.238)	0.054 (0.037)	0.094 (-0.082)	0.164 (-0.127)	0.272 (-0.210)	0.396 (-0.482)	0.163 (-0.045)

Source: Author's computations.