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FORECASTING INFLATION WITH A SIMPLE AND ACCURATE BENCHMARK: A CROSS COUNTRY ANALYSIS*

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Abstract

We explore the ability of several univariate models to predict inflation in a number of countries and at several forecasting horizons. We place special attention on forecasts coming from a family of ten seasonal models that we call the Driftless Extended Seasonal ARIMA (DESARIMA) family. Using out-of-sample Root Mean Squared Prediction Errors (RMSPE) we compare the forecasting accuracy of the DESARIMA models with that of traditional univariate time-series benchmarks available in the literature. Our results show that DESARIMA-based forecasts display lower RMSPE at short horizons for every single country, except one. We obtain mixed results at longer horizons. Roughly speaking, in half of the countries, DESARIMA-based forecasts outperform the benchmarks at long horizons. Remarkably, the forecasting accuracy of our DESARIMA models is surprisingly high in stable inflation countries, for which the RMSPE is barely higher than 100 basis points when the prediction is made 24- and even 36-months ahead.

Resumen

En este trabajo se explora la capacidad de varios modelos univariados para predecir la inflación de un conjunto de países a varios horizontes predictivos. Se pone especial atención en predicciones provenientes de una familia de diez modelos estacionales que es denominada Driftless Extended Seasonal ARIMA (DESARIMA). Mediante el cálculo de la raíz cuadrada del error cuadrático medio (RECM) fuera de muestra, se compara la capacidad predictiva de los modelos DESARIMA con la de modelos referenciales de series de tiempo tradicionalmente utilizados en la literatura. Los resultados indican que las predicciones basadas en modelos DESARIMA muestran una menor RECM para horizontes cortos en todos los países considerados, excepto en uno. Se obtienen resultados mixtos para horizontes mayores. Aproximadamente en la mitad de los países las predicciones basadas en modelos DESARIMA superan a los modelos referenciales en horizontes largos. Se destaca que la precisión predictiva de los modelos DESARIMA es sorprendentemente alta en países con inflación estable, para los cuales la RECM es algo mayor que 100 puntos base para predicciones realizadas a 24 y hasta 36 meses adelante.

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1 Introduction

Forecasts of economic and financial variables are usually important inputs for policy makers in the decision-making process. From time to time new forecasting techniques appear in the literature with the hope of providing a better understanding of the evolution of key economic variables or with the simpler goal of reducing some measure of forecasting error. When evaluating if a novel forecasting approach is useful for prediction, at least three elements are necessary: a measure of accuracy or loss function, a good enough benchmark against which to compare the new predictions, and third, an adequate test of predictive ability. In this work, we focus exclusively in the second point above, by introducing a family of methods for benchmarking inflation forecasts. This family, denominated Driftless Extended Seasonal ARIMA (DESARIMA), contains ten seasonal univariate time-series models sharing the common feature of a unit root.

These models produce competitive forecast at short and long forecast horizons when compared to traditional univariate benchmarks used in the literature. Besides accuracy, our DESARIMA family contains all the desirable features of well-behaved univariate time series models, but also some of their shortcomings. Between the main advantages of time series models, we want to mention that most of them are simple and tractable. Second, they rely only on lag values of the dependent variable and not on variables that sometimes may be difficult to find. Third, they can be updated easily and therefore out-of-sample analyses may be carried out in short time. Furthermore, as Aiolfi, Capistrán, and Timmermann (2011) point out, forecasts from time-series models can be used in combination with other procedures, including publicly-available surveys, greatly enhancing forecast accuracy. Pincheira (2012a, 2012b) shows that adjusted combinations between univariate time-series models and surveys can reduce the Root Mean Squared Prediction Error (RMSPE) of surveys substantially. The shortcomings of univariate time series models are well known. They include the omission of variables that may be relevant in the forecasting process, and their unsuitability to provide economic explanations of the forecasts they produce.

We evaluate our DESARIMA models in their ability to produce accurate forecasts of the Consumer Price Index (CPI) year-on-year (YoY) inflation for a number of countries, including both industrialized and developing economies.[1] We evaluate the forecasting performance of the DESARIMA family by comparing their out-of-sample RMSPE against a set of thirteen benchmark models commonly used in the literature. We also analyze the statistical significance of the differences between the best model of each family using the Giacomini and White (2006) test. The largest evaluation sample spans from February-1999 to December-2011 (155 observations) and include predictions made 1, 3, 6, 12, 24, and 36-months ahead.

We find that DESARIMA-based forecasts display lower out-of-sample RMSPE than forecasts coming from traditional benchmarks at short horizons for every single country in our sample, except Colombia. We obtain mixed results at longer horizons. Roughly speaking, in half of the countries DESARIMA-based forecasts outperforms traditional benchmarks at long horizons. Nevertheless, at these horizons, the behavior of the DESARIMA and

[1] The countries are Canada, Chile, Colombia, Israel, Mexico, Peru, South Africa, Sweden, Switzerland, Turkey, United Kingdom, and the United States.

benchmark models is relatively similar. Remarkably, the forecasting accuracy of our DESARIMA models is surprisingly high in stable inflation countries, for which the RMSPE is barely higher than 100 basis points when prediction is made 24 and even 36-months ahead.

The rest of the article is organized as follows. In section 2 we describe our econometric setup. In section 3 we describe the dataset. In section 4 we present and discuss the results of our forecast evaluation. Finally, section 5 concludes.

2 Econometric setup

In this paper we focus on monthly CPI YoY inflation defined as follows

$$\pi_t = \frac{CPI_t}{CPI_{t-12}} \cdot 100 - 100$$

We make use of models for this particular variable π_t, or for its first differences defined as

$$\Delta\pi_t = \pi_t - \pi_{t-1}$$

We are interested in h-step-ahead forecasts, where h takes the following values:

$$h \in \{1, 3, 6, 12, 24, 36\}$$

It is important to mention that for horizons longer than one month our forecasts are constructed dynamically. In the following two subsections we introduce the family of challenging and benchmarks models that we will use in our empirical application. The third subsection describes the framework we use to evaluate our forecasts.

2.1 Challenging models: DESARIMA family

For the construction of an alternative family of models we use as a start point two stylized facts characterizing the CPI: stochastic trend and seasonality. These facts are depicted in figure 1 by taking the representative case of the United Kingdom.

A general SARIMA specification allowing for stochastic trends and seasonality in the natural logarithm of the CPI provides our basic forecasting framework:

$$\Phi(L)\Phi_E(L^S)(1-L)^d(1-L^S)^D \ln(CPI_t) = \delta + \Theta_E(L^S)\Theta(L)\varepsilon_t \tag{1}$$

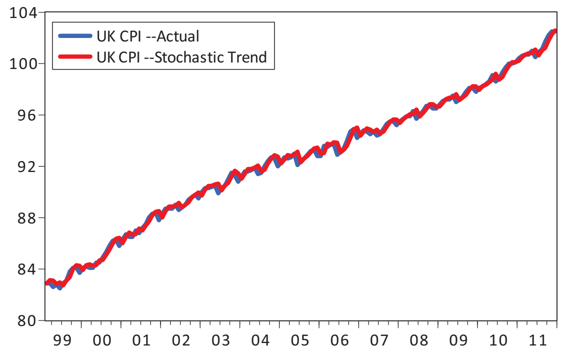
where

$$\begin{aligned}
\Phi(L) &= (1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p) \\
\Phi_E(L^S) &= (1 - \phi_{E1} L^S - \phi_{E2} L^{2S} - ... - \phi_{EP} L^{PS}) \\
\Theta(L) &= (1 - \theta_1 L - \theta_2 L^2 - ... - \theta_q L^q) \\
\Theta_E(L^S) &= (1 - \theta_{E1} L^S - \theta_{E2} L^{2S} - ... - \theta_{EQ} L^{QS})
\end{aligned}$$

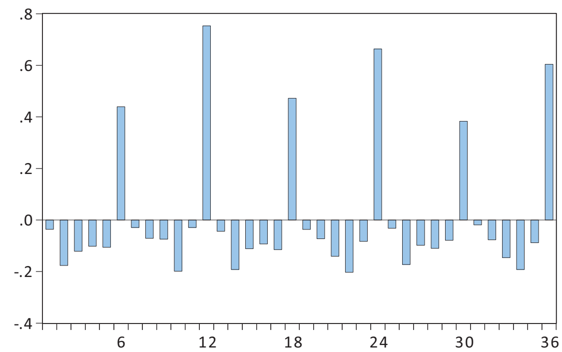
are the autoregressive (AR) and moving average (MA) lag operators that are supposed to be stationary and invertible, respectively. Here, L is a lag operator ($L^j x_t = x_{t-j}$), S represents the period of the series ($S = 12$ for monthly series), and δ, ϕ_j, ϕ_{Ej}, θ_j, and θ_{Ej} are parameters to be estimated. Finally, ε_t represents a white noise process with variance σ^2.

Figure 1: United Kingdom CPI –actual, trend, and seasonality

Actual and stochastic trend series



Autocorrelation function of detrended series



Source: Bank of England and authors' computations.

This specification captures the two aforementioned salient features of the CPI with some flexibility, by allowing both seasonal and nonseasonal trends, and also allowing both AR and MA components. Nevertheless, expression (1) represents a nonparsimonious specification (specially with long lag lengths) given the number of unknown parameters: one intercept, p nonseasonal autoregressive terms, q nonseasonal moving average terms, P seasonal autoregressive terms, and Q seasonal moving average terms. To alleviate the consequences of parameter uncertainty in our forecasts, we favor a parsimonious version of expression (1) by imposing the following restrictions on the lag operators:

$$p = P = q = Q = 1$$

We also impose, for simplicity,

$$d = 1 \text{ and } D = 0$$

Therefore, we have now the simpler expression:

$$(1 - \rho L)(1 - \phi L^{12})(1 - L)\ln(CPI_t) = \delta + (1 - \theta L)(1 - \theta_E L^{12})\varepsilon_t \tag{2}$$

in which the number of parameters is only five. Following Box and Jenkins (1970), Brockwell and Davis (1991) and Harvey (1993), we impose $\phi = 1$ to obtain an even more parsimonious expression as follows:

$$(1 - \rho L)(1 - L^{12})(1 - L)\ln(CPI_t) = \delta + (1 - \theta L)(1 - \theta_E L^{12})\varepsilon_t \tag{3}$$

This last expression is not only more parsimonious than expression (2), but also is more convenient because by using the following approximation

$$\pi_t \approx \ln(CPI_t) - \ln(CPI_{t-12})$$

we can write equation (3) directly in terms of π_t:

$$(1-\rho L)(\pi_t - \pi_{t-1}) = \delta + (1-\theta L)(1-\theta_E L^{12})\varepsilon_t$$

which is equivalent to:

$$\pi_t = \delta + (1+\rho)\pi_{t-1} - \rho\pi_{t-2} + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\varepsilon_{t-13}$$

Notice that this expression can also be written as

$$\pi_t - \pi_{t-1} = \delta + \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta_3\varepsilon_{t-13} \tag{4}$$

where $\theta_3 = \theta\theta_E$.

Expression (4) corresponds to an ARIMA(1,1,13) process for π_t in which several MA coefficients are set to zero. Following Box, Jenkins, and Reinsel (2008), the eventual or explicit form of the forecast function for (4) is given by:

$$\widehat{\pi}_{t+h|t} = c_t\rho^h + b_t + \left[\frac{\delta}{1-\rho}\right]h, \text{ for } h > 11 \tag{5}$$

where $\widehat{\pi}_{t+h|t}$ denotes the best linear h-step-ahead forecast of π_{t+h} given the information of the process available at time t. Furthermore, c_t and b_t represents adaptative coefficients, that is, coefficients that are stochastic and functions of the process at time t.[2]

From expression (5) we can see that long horizon forecasts of π_t will be divergent unless we impose the additional restriction of no intercept ($\delta = 0$).[3] This constraint leads us to the following specification:

$$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta_3\varepsilon_{t-13} \tag{6}$$

It is interesting to point out that some models commonly used in the literature are nested in expression (6). By taking $\rho = 0$ and $\theta = \theta_E = 0$, we recover the random walk (RW) used by Groen, Kapetanios and Price (2009), which is also similar to the naive model used by Atkeson and Ohanian (2001) for the United States. If we take only $\rho = 0$, expression (6) describes the *airline model* introduced by Box and Jenkins (1970), which has proved to be very useful to forecast monthly time series with seasonal patterns (Ghysels, Osborn, and Rodrigues, 2006). Finally, by taking $\rho = 0$ and $\theta_E = 0$ we recover the IMA(1,1) model used, among others, by Box, Jenkins, and Reinsel (2008) and more recently by Croushore (2010).

Expression (6) depends only on three unknown parameters: ρ, θ, and θ_E. We could define a family of eight models by considering the eight different variations of (6) in

[2]These adaptative terms are also function of the unknown parameters of the model.
[3]For a formal derivation and generalization of this result, see Pincheira and Medel (2012).

which we either include or exclude the terms multiplied by ρ, θ, and θ_E. None of this eight specifications, however, is capable to include two MA terms of orders 1 and 12 and simultaneously exclude the MA component of order 13. This is because $\theta_3 = \theta\theta_E$, so setting either $\theta = 0$ or $\theta_E = 0$ leads necessarily to $\theta_3 = 0$. It might be relevant to add a couple of models allowing for two moving average terms of orders 1 and 12 without the inclusion of a moving average term of order 13. This is so because in the particular case in which both coefficients θ and θ_E are small or close to zero, the parameter $\theta_3 = \theta\theta_E$ can be of negligible size, and its estimate could potentially be more harmful than useful, because our forecasts might be substantially contaminated with a noisy estimation. For this reason, we propose the following specification:

$$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\Upsilon\varepsilon_{t-13} \tag{7}$$

in which Υ can take the value 1 or 0. When $\Upsilon = 1$ we obtain the same family of eight models coming from expression (6). When $\Upsilon = 0$, however, we allow for the inclusion of the following two models:

$$\begin{aligned} 1.\ \pi_t - \pi_{t-1} &= \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} \\ 2.\ \pi_t - \pi_{t-1} &= \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} \end{aligned}$$

Because these two models do not have a direct SARIMA representation, we call our family of ten challenging models a Driftless Extended SARIMA family (DESARIMA). Table 1 provides the ten specifications belonging to our DESARIMA family.

Table 1: DESARIMA family

DESARIMA 1:	$\pi_t - \pi_{t-1} = \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12}$
DESARIMA 2:	$\pi_t - \pi_{t-1} = \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\varepsilon_{t-13}$
DESARIMA 3:	$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12}$
DESARIMA 4:	$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1} - \theta_E\varepsilon_{t-12} + \theta\theta_E\varepsilon_{t-13}$
DESARIMA 5:	$\pi_t - \pi_{t-1} = \varepsilon_t - \theta_E\varepsilon_{t-12}$
DESARIMA 6:	$\pi_t - \pi_{t-1} = \varepsilon_t$
DESARIMA 7:	$\pi_t - \pi_{t-1} = \varepsilon_t - \theta\varepsilon_{t-1}$
DESARIMA 8:	$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta_E\varepsilon_{t-12}$
DESARIMA 9:	$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t$
DESARIMA 10:	$\pi_t - \pi_{t-1} = \rho(\pi_{t-1} - \pi_{t-2}) + \varepsilon_t - \theta\varepsilon_{t-1}$

Source: Authors' elaboration.

2.2 Benchmark models

The use of different univariate time series models to generate forecasts is fairly usual in the forecasting literature in general, and in the inflation forecast literature in particular. For instance, Atkeson and Ohanian (2001) show that a simple variation of a RW model for YoY inflation in the United States is very competitive when predicting inflation 12-months ahead. Giacomini and White (2006), also for the United States, present an empirical application in which several CPI forecasts are compared to those generated by a RW with drift, and an autoregression in which the lag length is selected according to the Bayesian Information Criteria (BIC).

Another article using simple univariate benchmarks for the United States is Ang, Bekaert, and Wei (2007). Among the many methods the authors use, they include an ARMA(1,1) model, a RW, and an AR(p) model with lag length selection according to BIC. Elliot and Timmermann (2008) also explore the ability of several simple univariate models to predict inflation in the United States including a simple AR(p) model and a single exponential smoothing (ES), which generates the same forecasts as an IMA(1,1) model, in which some constraints are imposed over the parameters. More recently, Croushore (2010) also makes use of an IMA(1,1) model as a benchmark when evaluating survey-based inflation forecast for the United States.

Outside of the United States the use of univariate time-series models has also become fairly usual. Groen, Kapetanios, and Price (2009), for instance, evaluate the accuracy of the Bank of England inflation forecasts using several univariate models, including an AR(p) and the RW. Similarly, Andersson, Karlsson, and Svensson (2007) make use of simple time series models to compare inflation forecasts from the Riksbank. Finally, Pincheira and Alvarez (2009), and Pincheira (2010) also consider ARMA models to construct forecasts for Chilean inflation and GDP growth respectively.

Based on this selective review of the literature and our preliminary exploration, we define the family of benchmarks as that containing the following 13 univariate linear models for π_t: AR(1), AR(6), AR(12), ARMA(1,1), AR(p) with automatic lag selection based on the Akaike Information Criteria (AIC) and also on the BIC.[4] For this AR(p) process we consider different specifications varying p from 1 to $p^{max} = 12$. We also use ARMA(p,q) specifications with automatic lag selection according to AIC and BIC with $p^{max} = 12$ and $q^{max} = 6$. In addition we include the models labeled 3 and 4 in Capistrán, Constandse, and Ramos-Francia (2010) that include specific regressors for seasonality (henceforth CCR-F).[5] Finally, we also include a single and double ES, and a Holt-Winters model with additive seasonal components. These benchmark models are summarized in table 2.

The models (9) and (10) from CCR-F contains the lag polynomial $\varphi(L)$. Its order is determined according to BIC. In table 2, D_{it} represents a seasonal dummy variable for the i^{th} month. For models (11) to (13) the initial value of inflation ($\widehat{\pi}_0$) is determined as the average of the first half of the estimation sample.

2.3 Forecast evaluation framework

We carry out an out-of-sample evaluation of our benchmark and DESARIMA models. To describe this evaluation, let us assume that for a given country we have $T+1$ observations of π_t. 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. Finally they are compared with 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+1+h}. We iterate like this until the last forecasts are built using the last

[4] The BIC is defined as $BIC = -2(\ell/T) + 2(k/T)$, whereas the AIC is defined as $AIC = -2(\ell/T) + k \cdot log(T)/T$, where ℓ is the log likelihood function, k the number of unknown parameters, and T the sample size. Therefore, the only difference in estimating the true order of an ARMA models is the penalty term imposed to the number of unknown parameters. For more details, see Akaike (1974) and Schwarz (1978).

[5] One of the models in Capistrán, Constandse, and Ramos-Francia (2010) is defined in terms of π (model 3), while the other is defined in terms of $\Delta\pi$.

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:

$$\widehat{\mathsf{RMSPE}}_h = \left[\frac{1}{P(h)} \sum_{t=R}^{T+1-h} (\pi_{t+h} - \widehat{\pi}_{t+h|t})^2 \right]^{\frac{1}{2}}$$

where $\widehat{\pi}_{t+h|t}$ 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 the models with the best performance within each family. By doing this, we acknowledge that our inference approach does not control for a familywise false discovery rate. Methods to correctly control for a familywise type-I error between two families of models are subject of current research, and some unpublished papers are making progress in this direction (see for instance Calhoun, 2011, and Pincheira, 2011).

Inference is carried out within the framework developed by Giacomini and White (2006) (henceforth GW). We 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 forecasting methods instead of two competing models. This is highly desirable for our purposes, which is purely focused on the forecasts that different time-series models can deliver.

Once the best forecasting models within each family are chosen, we test the following null hypothesis

$$\mathsf{NH} : \mathbb{E}(d_h) \leq 0$$

against the alternative

$$\mathsf{AH} : \mathbb{E}(d_h) > 0$$

where

$$d_t(h) = (\pi_{t+h} - \widehat{\pi}_{t+h|t}^{Benchmark})^2 - (\pi_{t+h} - \widehat{\pi}_{t+h|t}^{DESARIMA})^2$$

We test the null hypothesis of superior predictive ability in favor of the family of traditional benchmarks. Accordingly, we use a one-sided version of the t-type test statistic proposed by GW.

Table 2: Benchmark models

1. AR(1) with intercept	$\pi_t = \delta + \rho_1 \pi_{t-1} + \varepsilon_t.$	11. Single ES	$\widehat{\pi}_t = \alpha\pi_{t-1} + (1-\alpha)\widehat{\pi}_{t-1}$, $0 < \alpha < 1.$
2. AR(6) with intercept	$\pi_t = \delta + \sum_{i=1}^{6}\rho_i \pi_{t-i} + \varepsilon_t.$	12. Double ES	$\widehat{\pi}_{t+h} = \left(2 + \frac{\alpha h}{1-\alpha}\right) S_t - \left(1 + \frac{\alpha h}{1-\alpha}\right) D_t,$
3. AR(12) with intercept	$\pi_t = \delta + \sum_{i=1}^{12}\rho_i \pi_{t-i} + \varepsilon_t.$		$= 2S_t - D_t + \frac{\alpha}{1-\alpha}(S_t - D_t)h,$
4. ARMA(1,1) with intercept	$\pi_t = \delta + \rho_1 \pi_{t-1} - \theta_1 \varepsilon_{t-1} + \varepsilon_t.$		$S_t = \alpha\pi_t + (1-\alpha)S_{t-1},$
5. AR(12) BIC-based	$\pi_t = \delta + \sum_{i=1}^{12}\rho_i \pi_{t-i} + \varepsilon_t.$		$D_t = \beta S_t + (1-\beta)D_{t-1}$, $\alpha = \beta.$
6. AR(12) AIC-based	$\pi_t = \delta + \sum_{i=1}^{12}\rho_i \pi_{t-i} + \varepsilon_t.$	13. Holt-Winters	$\widehat{\pi}_{t+h} = a_t + b_t h + c_{t+h-s},$
7. ARMA(12,6) BIC-based	$\pi_t = \delta + \sum_{i=1}^{12}\rho_i \pi_{t-i} - \sum_{j=1}^{6}\theta_j \varepsilon_{t-j} + \varepsilon_t.$		$a_t = \alpha(\pi_t - c_{t-s}) + (1-\alpha)(a_{t-1} + b_{t-1}),$
8. ARMA(12,6) AIC-based	$\pi_t = \delta + \sum_{i=1}^{12}\rho_i \pi_{t-i} - \sum_{j=1}^{6}\theta_j \varepsilon_{t-j} + \varepsilon_t.$		$b_t = \beta(a_t - a_{t-1}) + 1 - \beta b_{t-1},$
9. CCR-F | Model 3	$\varphi(L)(\pi_t - \pi_{t-1}) = \sum_{i=1}^{12}\mu_i D_{it} + \varepsilon_t.$		$c_t = \gamma(\pi_t - a_{t+1}) - \gamma c_{t-s},$
10. CCR-F | Model 4	$\varphi(L)\pi_t = \sum_{i=1}^{12}\mu_i D_{it} + \kappa t + \varepsilon_t.$		$0 < \alpha, \beta, \gamma < 1.$

The parameters δ, ρ_i, θ_j, μ_i, and κ, are estimated. $\varphi(L)$ is a lag polynomial whose order is determined by BIC. The parameters α, β, and γ, are chosen jointly by minimizing the in-sample mean squared error. h is the forecast horizon, and s is the seasonal frequency. When applies, $\varepsilon \sim iid\mathcal{N}(0, \sigma^2_\varepsilon)$. Source: Authors' elaboration.

3 Our dataset

We use monthly CPI inflation data for Canada, Chile, Colombia, Israel, Mexico, Peru, South Africa, Sweden, Switzerland, Turkey, United Kingdom, and the United States, covering the period September 1990-December 2011. This is a subsample of inflation targeting countries plus the US. We select this subsample of inflation targeting countries (plus the US) by making sure that they all have data at a monthly frequency and they all have sufficiently long series to carry out an out-of-sample analysis covering the same sample period. The source of the dataset are country-specific central banks. This implies that despite some CPI market basket changes experimented by some countries during the sample period, we use the same official inflation observations used by policymakers. The target variable corresponds to YoY CPI. Some descriptive statistics of all the series for different samples are shown in appendix A.

Table 3 shows results of traditional unit root tests for our target variables for the sample period from September-1990 to December-2011. For most of the countries it is not possible to reject the null hypothesis of a unit root at usual significance levels. Some exceptions are Canada, Mexico, Sweden and the United States. The evidence for the first difference in inflation is, however, quite robust. In this case the null hypothesis of a unit root is always rejected.

Note that some of the countries in our sample have converged to a seemingly stationary inflation process after experiencing a relatively long period of declining inflation. This mixture of regimes represents a special challenge to any device aiming at forecasting inflation during this sample period. Besides, we have considered a relatively heterogeneous set of countries. This is clearly showed in figure 2, in which we depict separately countries with low- and high-inflation We will see in future sections that despite this heterogeneity our DESARIMA family works well.

Table 3: Unit root testing –full sample

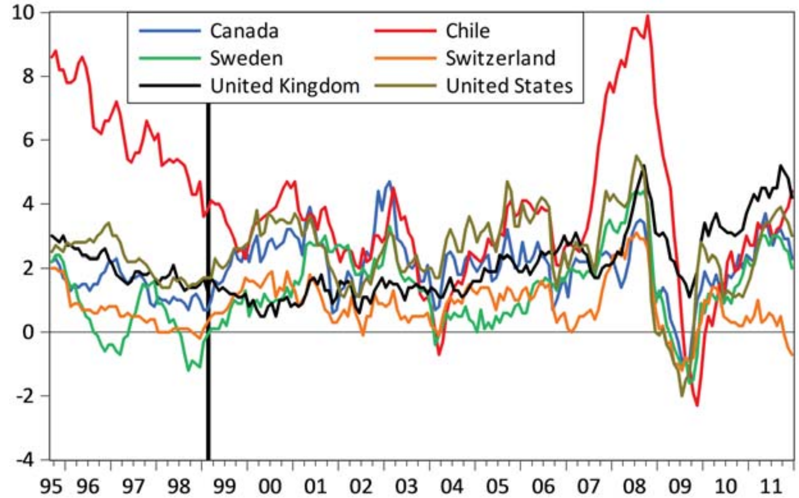
	Level (π_t)				First differences ($\pi_t - \pi_{t-1}$)			
	ADF	DFGLS	PP	KPSS	ADF	DFGLS	PP	KPSS
Canada	-3.903**	-1.389	-3.680**	0.133*	-8.350***	-0.962	-14.337***	0.063
Chile	-2.328	-0.586	-2.104	0.405***	-5.069***	-2.102	-12.083***	0.400*
Colombia	-1.913	-2.002	-1.570	0.396***	-9.782***	-7.939***	-9.648***	0.134
Israel	-3.118	-2.916	-2.488	0.362***	-9.045***	-1.750	-8.783***	0.067
Mexico	-3.816**	-3.819***	-2.692	0.097	-4.451***	-3.910***	-5.095***	0.037
Peru	-1.930	-0.469	-2.156	0.340***	-6.368***	-1.609	-9.895***	0.295
South Africa	-2.139	-1.581	-2.894	0.231***	-7.030***	-4.762***	-10.974***	0.051
Sweden	-4.219***	-0.746	-2.760	0.292***	-7.985***	-4.084***	-15.384***	0.197
Switzerland	-2.127	-1.855	-2.522	0.311***	-9.701***	-1.465	-15.167***	0.058
Turkey	-2.392	-1.171	-2.764	0.241***	-7.678***	-0.724	-16.425***	0.106
United Kingdom	-1.678	-0.908	-1.857	0.399***	-14.347***	-1.459	-14.402***	0.270
United States	-3.523**	-1.825	-3.683**	0.112	-9.672***	-1.703	-10.488***	0.041

* p<10%, ** p<5%, *** p<1%. ADF denote the Augmented Dickey-Fuller test, DFGLS the GLS detrended Dickey-Fuller test (Elliot, Rothenberg, and Stock), PP the Phillips-Perron test, and KPSS the Kwiatkowski, Phillips, Schmidt, and Shin test. The null hypothesis for ADF, DFGLS, and PP tests is the series has an unit root. For KPSS test the null hypothesis is the series is stationary.

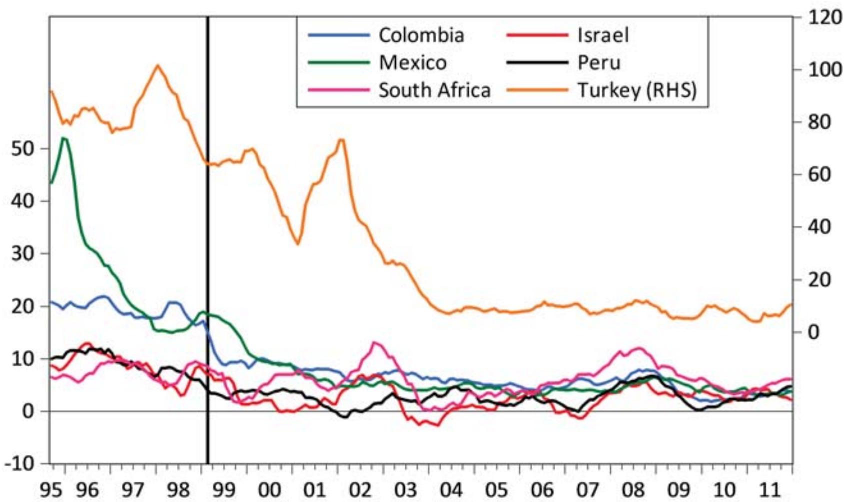
Source: Authors' computations.

Figure 2: Inflation of CPI

A: Low-inflation countries



B: High-inflation countries



Vertical line: Evaluation sample startpoint (Feb-1999). Source: Country-specific central banks.

We estimate the models with a fixed-size rolling window of length R. Because the exact choice of the rolling window size may play an important role in the accuracy of our forecasts, we generate predictions when R is set to 40 and 100. Our first estimation window of 40 observations covers the period from September-1995 to January-1999. When $R = 100$, the first estimation window covers the period from September-1990 to January-1999. The rest of the sample is used to compute forecast errors. We focus on 1, 3, 6, 12, 24 and 36-months-ahead forecasts. Accordingly, we have a total of 155 observations for 1-step-ahead forecast errors, 153 observations for 3-step-ahead forecast errors, 150 for 6-step-ahead forecast errors, 144 for 12-step-ahead forecast errors, 132 for 24-step-ahead forecast errors, and 120 observations for 36-steps-ahead forecasts errors. The results of our out-of-sample evaluation follow next.

4 Empirical results

In a huge empirical exercise, like the one we have carried out in this paper, there are a number of interesting findings that deserve mentioning. We will organize our discussion around four major topics: short-horizon accuracy, long-horizon accuracy, robustness check, and the role of the estimation window size. In appendix B we show the RMSPE estimates for all the models under evaluation. We also report the GW core statistic and its respective t-statistic when comparing the best models within each family.

4.1 Short-horizon accuracy

In table 4 we show sample RMSPE results for the best models within each family. These RMSPE are also depicted in figure 3. Notice that for the construction of this figure and table, the DESARIMA family includes the forecasts coming from 20 forecasting methods. These forecasting methods correspond to each DESARIMA model estimated with either R=40 or R=100 observations. Similarly, the benchmark family contains 26 forecasting methods coming from the 13 benchmark models estimated with either R=40 or R=100 observations. From table 4 we see that the best DESARIMA method always outperform the best benchmark method when forecasting 1- and 3-months-ahead. A similar result holds true 6-months-ahead, Colombia being the only exception. Furthermore, in only three countries (Canada, Colombia, and Mexico) differences in favor of the best DESARIMA model are not statistically significant. In summary, the best DESARIMA forecast are almost always more accurate than the best benchmark forecast at short horizons. Table 6 indicates how frequent a given model generates the most accurate forecasts within each family. It is interesting to note that the most frequent winners at short horizons (1- and 3- months-ahead) within the DESARIMA family are the models labeled DESARIMA 4, 5, and 8, which are different from the more traditional IMA(1,1), RW, and airline model, which corresponds to those labeled as DESARIMA 7, 6, and 2, respectively.

4.2 Long-horizon accuracy

Table 4 depicts a different scenario when forecasting at the longer horizons of 12, 24, and 36-months-ahead. Results are mixed and no clear winner between the two families under consideration arises from this table. In fact, we see that in seven countries the best forecasting methods one-year-ahead belongs to the DESARIMA family. Regarding two- and three-years-ahead forecasts, table 4 shows that only in five countries the lowest RMSPE is achieved by the DESARIMA family. It is interesting to note, however, that in percentage terms forecasts from the two families are relatively similar at longer horizons. It is also important to mention that in some cases the RMSPE achieved at long horizons is remarkably low. For instance, for the cases of Canada, Switzerland, and the United Kingdom, the RMSPE of the best models is lower than 100 basis points when forecasting three-years-ahead. Finally, from table 6 we see that the most frequent winner at long horizons within the DESARIMA family is the DESARIMA 9 model.

4.3 Robustness check

Our previous analysis is focused on finding the best forecasting model within a set of forecasting methods. This task may be hard. Furthermore, our previous results may be questioned on the grounds of the method we have used to carry out inference about predictive ability. As we have not implemented methods to adequately control for the familywise type-I error rate, our inference may not be precise enough. To overcome these shortcomings we also consider the median forecast coming from the 20 DESARIMA methods and from the 26 benchmarks methods. In table 5 and figure 4 we report the RMSPE of these forecasts. From table 5 we see that the median DESARIMA forecast always outperform the median benchmark forecasts at 1 and 3-months-ahead. A similar result holds true 6-months-ahead, Mexico being the only exception. At longer horizons table 5 shows that in only five countries there are cases in favor of the benchmark methods: Colombia, Israel, Turkey, Mexico, and the United Kingdom. Therefore, at these horizons results are mixed again, but leaning in favor of the DESARIMA forecasts as in 7 out of 12 countries the median DESARIMA forecast outperforms the median benchmark forecast at every single horizon.

4.4 The role of the estimation window size (R)

We finally investigate the role that the size of the estimation window R may have in the accuracy of our forecasts. In stationary environments we should expect a higher predictive performance of the methods estimated with longer samples. Nevertheless, an environment in which parameters are time-varying may be better handled by shorter estimation windows. Table 8 shows how frequent each model produces better forecasts when estimated within rolling windows of only 40 observations. For most of the benchmarks models these rates are lower than 50%, and sometimes much lower, indicating that in general they produce better forecasts when they are estimated with rolling windows of 100 observations. The only exceptions are the single and double ES, for which at a few forecasting horizons we find a better performance when estimated with only 40 observations.

Results from the DESARIMA family are different. In fact the models labeled DESARIMA 2, 3, 5, and 8, show frequency rates greater or equal than 50% at every single horizon. For the rest of the models within the DESARIMA family, rates are not that high but in general are higher than in the benchmark family. In fact, the average rate of the DESARIMA family is 49%. This is in sharp contrast with the average rate of the benchmark family, which is only 22%. This indicates that the estimation window size seems to play a major role within the benchmark family and not in the challenging DESARIMA family.

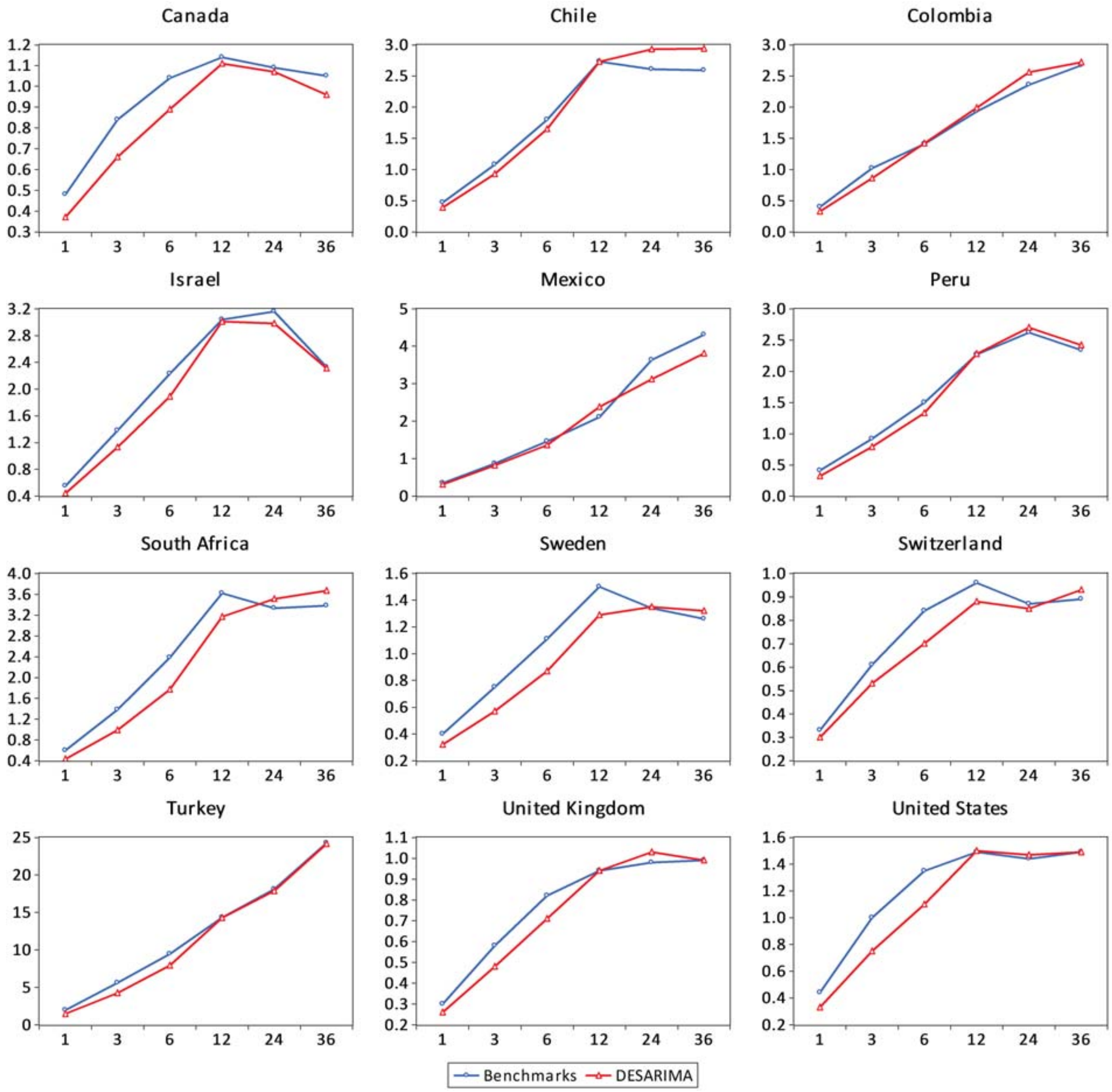
5 Concluding remarks

In this paper we introduce a family of univariate forecasting models that are shown to produce competitive inflation forecasts both at short and long horizons. This family of models is called Driftless Extended Seasonal ARIMA (DESARIMA) and contains ten seasonal driftless univariate time-series models sharing the common feature of a unit root.

Using out-of-sample Root Mean Squared Prediction Errors (RMSPE) we compare the forecasting accuracy of the DESARIMA models with that of traditional univariate time-series benchmarks for a sample of 12 countries. Our results show that DESARIMA-based forecasts display lower RMSPE at short horizons for every single country. We obtain mixed results at longer horizons. Roughly speaking, in half of the countries, DESARIMA-based forecasts outperform the benchmarks at long horizons. Remarkably, the forecasting accuracy of our DESARIMA models is surprisingly high in stable inflation countries, for which the RMSPE is barely higher than 100 basis points when prediction is made 24- and even 36-months-ahead. These results also hold true when we compare the DESARIMA family and our set of benchmarks in terms of their median forecasts. Finally, we analyze the impact of the estimation window size on the accuracy of our forecasts. We do this by estimating all the models with two different sample sizes of 40 and 100 observations. While the traditional benchmarks tend to benefit from the increasing number of observations, this is less clear cut in the case of our DESARIMA based forecasts. In fact, at least 4 out of 10 DESARIMA models tend to generate more accurate forecasts when only 40 observations are used to estimate the models.

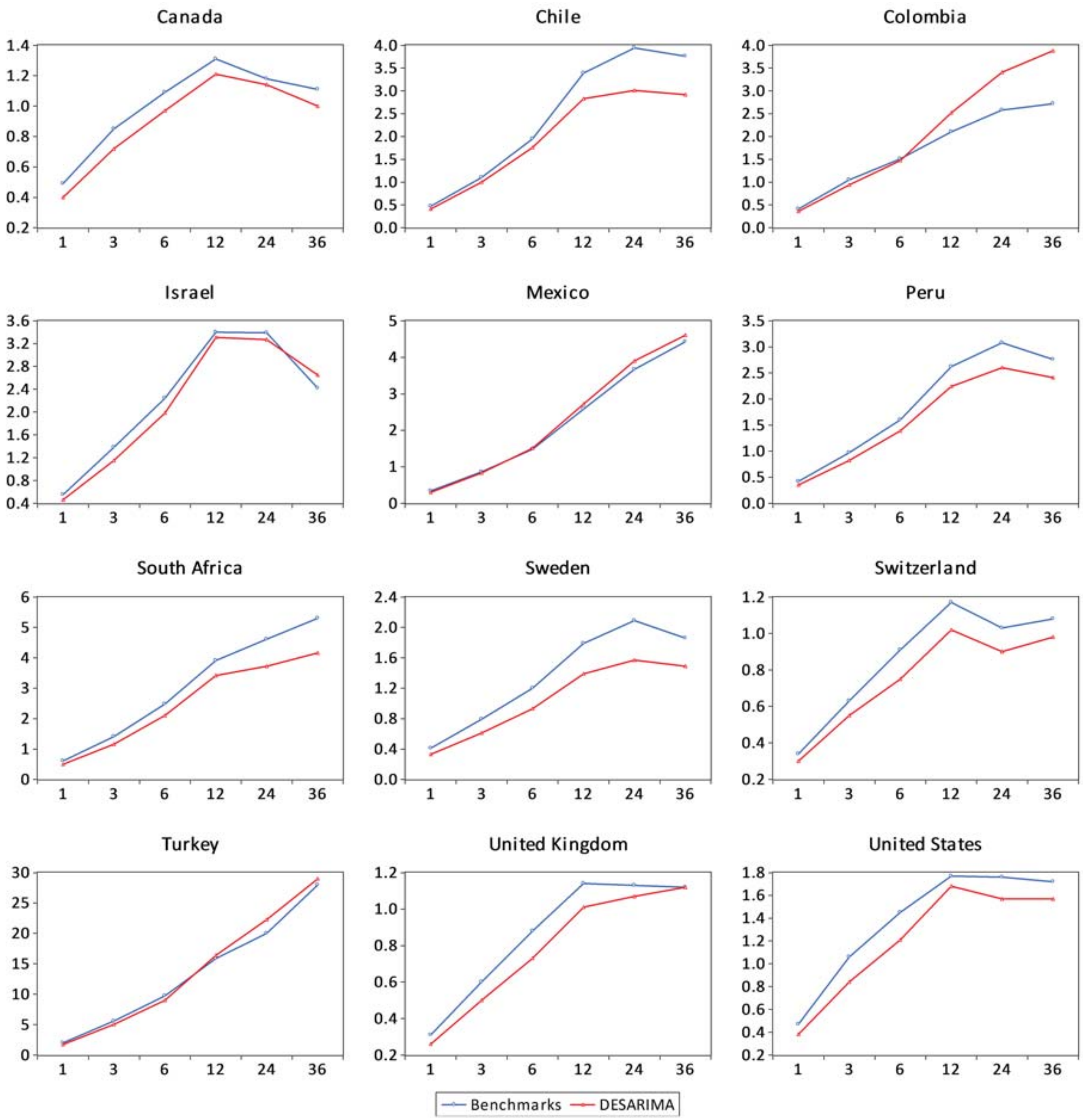
A horse race between our DESARIMA family and more complex benchmarks seem to be an interesting issue to explore in subsequent research. Likewise, the construction of a multivariate DESARIMA family might also be of interest for future investigation.

Figure 3: RMSPE of the best model of each family across horizons



Source: Authors' elaboration.

Figure 4: RMSPE of the median forecast of each family across horizons



Source: Authors' elaboration.

Table 4: Multi-horizon RMSPE estimates of the best model across R

	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
	Canada						**South Africa**					
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(6)	AR [BIC]	AR(12)	AR(6)	AR(12)	AR(12)	AR [BIC]	AR [AIC]	ARMA [AIC]
RMSPE	0.482	0.836	1.044	1.140	1.087	1.047	0.605	1.379	2.378	3.625	3.334	3.380
Best DESARIMA	[5]	[5]	[5]	[5]	[1]	[2]	[4]	[4]	[4]	[4]	[8]	[5]
RMSPE	0.366***	0.658**	0.890	1.105	1.068	0.957**	0.434***	0.985***	1.768**	3.170*	3.508	3.674
	Chile						**Sweden**					
Best benchmark	AR [AIC]	AR(6)	AR(6)	AR(6)	AR(6)	AR(6)	AR(1)	ARMA(1,1)	AR(6)	AR(6)	AR(12)	AR(6)
RMSPE	0.466	1.083	1.800	2.731	2.608	2.589	0.398	0.754	1.110	1.499	1.342	1.265
Best DESARIMA	[4]	[8]	[8]	[8]	[4]	[2]	[5]	[3]	[3]	[1]	[5]	[5]
RMSPE	0.392***	0.931**	1.695**	2.730	2.931	2.942	0.318***	0.569***	0.868***	1.292	1.347	1.315
	Colombia						**Switzerland**					
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(6)	AR [AIC]	ARMA [AIC]	ARMA [AIC]	ARMA [AIC]	ARMA(1,1)	AR [AIC]	AR [BIC]
RMSPE	0.404	1.018	1.407	1.930	2.360	2.669	0.330	0.612	0.840	0.959	0.866	0.892
Best DESARIMA	[8]	[8]	[8]	[7]	[7]	[9]	[3]	[1]	[4]	[4]	[3]	[1]
RMSPE	0.333**	0.860*	1.417	1.988	2.559	2.715	0.295**	0.531***	0.700**	0.878*	0.846	0.927
	Israel						**Turkey**					
Best benchmark	AR(12)	AR(12)	ARMA(1,1)	ARMA(1,1)	AR [BIC]	AR(12)	AR [AIC]	CCR-F | M3	ES [Single]	ES [Single]	ES [Single]	ES [Single]
RMSPE	0.552	1.376	2.302	3.043	3.159	2.329	1.945	5.590	9.442	14.319	18.092	24.270
Best DESARIMA	[8]	[8]	[8]	[1]	[1]	[1]	[8]	[8]	[8]	[7]	[9]	[9]
RMSPE	0.436***	1.133***	1.891**	3.007	2.979	2.312	1.449***	4.237**	7.919**	14.271	17.867	21.149
	Mexico						**United Kingdom**					
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	CCR-F | M3	ES [Single]	ES [Single]	ES [Single]	ES [Single]	AR [AIC]	AR [AIC]	AR [AIC]	ES [Single]
RMSPE	0.348	0.872	1.416	2.115	3.640	4.305	0.303	0.576	0.822	0.942	0.978	0.995
Best DESARIMA	[1]	[1]	[9]	[9]	[9]	[9]	[2]	[2]	[2]	[1]	[1]	[6]
RMSPE	0.315**	0.818*	1.357	2.380	3.115*	3.813*	0.259***	0.485**	0.711**	0.944	1.030	0.995
	Peru						**United States**					
Best benchmark	AR(6)	AR(6)	ES [Single]	ES [Single]	AR [AIC]	AR [AIC]	ARMA [AIC]	ARMA [AIC]	ARMA(1,1)	AR [AIC]	ARMA [BIC]	ARMA(1,1)
RMSPE	0.415	0.921	1.503	2.267	2.619	2.339	0.442	1.003	1.350	1.490	1.438	1.492
Best DESARIMA	[4]	[8]	[8]	[8]	[3]	[6]	[4]	[4]	[4]	[5]	[4]	[3]
RMSPE	0.325***	0.791**	1.329*	2.276	2.698	2.417	0.331***	0.751**	1.099**	1.495	1.471	1.487

See tables 1 and 2 for DESARIMA and benchmark specifications. Shaded cells indicates that minimum RMSPE is achieved with R=40.

GW test: * p<10%, ** p<5%, *** p<1%. Source: Authors' computations.

Table 5: Multi-horizon RMSPE estimates of the median forecasts across R

	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
	Canada						South Africa					
RMSPE benchmark	0.493	0.852	1.088	1.307	1.185	1.107	0.613	1.411	2.476	3.910	4.613	5.297
RMSPE DESARIMA	0.399***	0.716**	0.973	1.209**	1.144	1.002**	0.496***	1.163***	2.099***	3.421**	3.721***	4.161***
	Chile						Sweden					
RMSPE benchmark	0.469	1.099	1.951	3.393	3.944	3.757	0.406	0.787	1.203	1.786	2.089	1.863
RMSPE DESARIMA	0.408***	1.003*	1.760*	2.828*	3.014**	2.924**	0.334***	0.608***	0.932**	1.392**	1.572***	1.489***
	Colombia						Switzerland					
RMSPE benchmark	0.410	1.046	1.506	2.105	2.575	2.717	0.340	0.634	0.914	1.166	1.028	1.083
RMSPE DESARIMA	0.356***	0.942*	1.474	2.524	3.412	3.881	0.302***	0.550***	0.748***	1.017*	0.895**	0.977*
	Israel						Turkey					
RMSPE benchmark	0.553	1.379	2.242	3.396	3.386	2.418	1.999	5.570	9.699	15.869	20.024	27.982
RMSPE DESARIMA	0.463***	1.154***	1.976***	3.313	3.269	2.646	1.718***	5.016**	8.979**	16.396	22.263	28.969
	Mexico						United Kingdom					
RMSPE benchmark	0.344	0.864	1.478	2.584	3.675	4.427	0.308	0.604	0.881	1.142	1.132	1.118
RMSPE DESARIMA	0.305***	0.825*	1.510	2.720	3.899	4.609	0.259***	0.497***	0.735***	1.013	1.071	1.118
	Peru						United States					
RMSPE benchmark	0.424	0.973	1.601	2.617	3.079	2.757	0.471	1.055	1.454	1.771	1.757	1.722
RMSPE DESARIMA	0.352***	0.825***	1.393***	2.240**	2.604*	2.414	0.380***	0.844***	1.212**	1.682**	1.570*	1.574**

See tables 1 and 2 for DESARIMA and benchmark and specifications.

GW test: * $p<10\%$, ** $p<5\%$, *** $p<1\%$. Source: Authors' computations.

Table 6: Percentage of times that a model is the best by family

	R=40						R=100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	8%	8%	0%	0%	0%	17%	8%	0%	0%	0%	0%	0%
2. AR(6)	8%	17%	8%	8%	8%	8%	17%	17%	25%	25%	17%	17%
3. AR(12)	0%	0%	0%	0%	0%	0%	8%	17%	8%	0%	8%	17%
4. ARMA(1,1)	42%	25%	33%	8%	8%	8%	17%	25%	33%	25%	0%	17%
5. AR(12) [BIC]	0%	0%	0%	25%	17%	8%	8%	0%	0%	8%	8%	8%
6. AR(12) [AIC]	8%	0%	8%	8%	25%	8%	8%	0%	0%	17%	25%	8%
7. ARMA(12,6) [BIC]	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	8%	0%
8. ARMA(12,6) [AIC]	0%	0%	0%	0%	0%	0%	17%	17%	8%	0%	8%	8%
9. CCR-F | M3	0%	0%	0%	8%	0%	0%	8%	8%	0%	0%	0%	0%
10. CCR-F | M4	0%	0%	0%	0%	0%	0%	0%	0%	8%	8%	0%	0%
11. Single ES	25%	42%	50%	42%	42%	50%	8%	17%	17%	17%	25%	25%
12. Double ES	8%	8%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
13. Holt-Winters	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
1. DESARIMA 1	8%	8%	17%	25%	33%	8%	8%	33%	17%	17%	17%	17%
2. DESARIMA 2	8%	8%	17%	8%	8%	33%	0%	0%	0%	0%	0%	8%
3. DESARIMA 3	0%	0%	0%	0%	17%	0%	8%	8%	8%	8%	0%	8%
4. DESARIMA 4	17%	8%	8%	0%	8%	0%	42%	33%	42%	25%	25%	8%
5. DESARIMA 5	17%	8%	0%	8%	8%	8%	17%	8%	8%	17%	8%	17%
6. DESARIMA 6	0%	0%	0%	0%	0%	17%	0%	0%	0%	8%	17%	17%
7. DESARIMA 7	0%	0%	0%	17%	17%	8%	0%	0%	8%	8%	0%	0%
8. DESARIMA 8	50%	58%	50%	33%	0%	8%	25%	17%	8%	0%	8%	0%
9. DESARIMA 9	0%	0%	8%	8%	0%	17%	0%	0%	8%	8%	25%	25%
10. DESARIMA 10	0%	8%	0%	0%	8%	0%	0%	0%	0%	8%	0%	0%
	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

See tables 1 and 2 for DESARIMA and benchmark and specifications.

Shaded cells indicate the best performance within a horizon by family.

Source: Authors' computations.

Table 7: Percentage of times that a model estimated with any R is the best across families

	h=1	h=3	h=6	h=12	h=24	h=36
R=40	33%	42%	50%	33%	17%	8%
R=100	67%	58%	50%	67%	83%	92%

Shaded cells indicate the best performance within a horizon.

Source: Authors' computations.

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Appendix

A Descriptive statistics of the series

Descriptive statistics –three samples

	Larger estimation sample				Evaluation sample				Full sample			
	Sep-1990 | Jan-1999				Feb-1999 | Dec-2011				Sep-1990 | Dec-2011			
	Mean	Std. Dev.	Max.	Min.	Mean	Std. Dev.	Max.	Min.	Mean	Std. Dev.	Max.	Min.
Canada	2.00	1.70	6.90	-0.20	2.10	0.90	4.70	-0.90	2.10	1.30	6.90	-0.90
Chile	11.70	6.50	30.40	3.60	3.30	2.20	9.90	-2.30	6.60	6.00	30.40	-2.30
Colombia	23.00	4.30	32.40	16.40	6.00	2.40	15.40	1.80	12.70	8.90	32.40	1.80
Israel	11.50	4.20	21.60	3.00	2.40	2.30	7.00	-2.70	6.00	5.50	21.60	-2.70
Mexico	20.60	11.20	52.00	6.70	5.80	3.40	18.50	2.90	11.60	10.40	52.00	2.90
Peru	9.60	2.10	13.70	5.10	2.60	1.60	6.70	-1.10	4.30	3.40	13.70	-1.10
South Africa	10.10	3.30	16.70	4.90	5.80	2.90	13.10	0.10	7.50	3.70	16.70	0.10
Sweden	3.00	3.40	12.60	-1.20	1.50	1.20	4.40	-1.60	2.10	2.40	12.60	-1.60
Switzerland	2.30	2.10	6.60	-0.20	0.90	0.80	3.10	-1.20	1.40	1.60	6.60	-1.20
Turkey	81.20	17.40	130.90	54.50	23.70	22.50	73.10	4.00	46.40	34.90	130.90	4.00
United Kingdom	3.30	2.10	8.50	1.30	2.10	1.10	5.20	0.50	2.60	1.70	8.50	0.50
United States	2.90	1.10	6.40	1.40	2.50	1.30	5.50	-2.00	2.70	1.20	6.40	-2.00

Source: Authors' computations.

B Sample RMSPE estimates

B.1 Canada

Canada: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.493	0.843	1.086	1.275	1.191	1.060	0.487	0.837	1.068	1.231	1.106	1.086
2. AR(6)	0.522	0.936	1.164	1.336	1.213	1.251	0.497	0.860	1.074	1.140	1.098	1.064
3. AR(12)	0.552	1.059	1.560	1.703	2.092	1.307	0.518	0.940	1.230	1.307	1.271	1.047
4. ARMA(1,1)	0.505	0.850	1.080	1.266	1.108	1.296	0.482	0.836	1.044	1.179	1.095	1.078
5. AR(12) [BIC]	0.509	0.867	1.099	1.263	1.178	1.076	0.490	0.845	1.062	1.196	1.087	1.061
6. AR(12) [AIC]	0.517	0.941	1.215	1.270	1.110	1.297	0.514	0.915	1.210	1.283	1.243	1.099
7. ARMA(12,6) [BIC]	0.578	0.974	1.155	1.312	1.149	1.424	0.531	0.902	1.113	1.215	1.104	1.085
8. ARMA(12,6) [AIC]	0.588	1.100	1.318	1.379	1.380	1.379	0.495	0.951	1.212	1.345	1.267	1.123
9. CCR-F | M3	0.605	1.055	1.425	1.825	2.094	1.761	0.522	0.954	1.304	1.717	1.832	1.632
10. CCR-F | M4	0.616	1.115	1.466	1.861	2.326	2.512	0.521	0.906	1.157	1.326	1.209	1.277
11. Single ES	0.499	0.886	1.202	1.557	1.470	1.128	0.493	0.886	1.206	1.560	1.476	1.130
12. Double ES	0.604	1.190	1.939	3.587	5.931	7.423	0.568	1.191	2.024	3.811	6.538	8.383
13. Holt-Winters	0.615	1.100	1.546	2.011	2.081	2.303	0.524	0.950	1.296	1.585	1.538	1.449
1. DESARIMA 1	0.394	0.719	0.979	1.210	1.116	1.054	0.368	0.660	0.894	1.111	1.068	0.968
2. DESARIMA 2	0.403	0.719	0.984	1.208	1.143	1.045	0.368	0.661	0.894	1.114	1.075	0.957
3. DESARIMA 3	0.405	0.746	1.003	1.342	1.324	1.286	0.366	0.665	0.923	1.142	1.095	0.976
4. DESARIMA 4	0.406	0.722	0.991	1.212	1.149	1.050	0.369	0.670	0.914	1.150	1.093	1.001
5. DESARIMA 5	0.396	0.721	0.982	1.208	1.139	1.047	0.366	0.658	0.890	1.105	1.073	0.969
6. DESARIMA 6	0.493	0.886	1.206	1.560	1.476	1.130	0.493	0.886	1.206	1.560	1.476	1.130
7. DESARIMA 7	0.512	0.899	1.212	1.573	1.494	1.136	0.493	0.892	1.215	1.578	1.501	1.858
8. DESARIMA 8	0.403	0.721	0.988	1.214	1.142	1.046	0.368	0.662	0.899	1.110	1.074	0.971
9. DESARIMA 9	0.504	0.895	1.213	1.573	1.488	1.136	0.493	0.889	1.212	1.577	1.496	1.144
10. DESARIMA 10	0.504	0.885	1.195	1.545	1.506	1.503	0.499	0.896	1.211	1.578	1.478	1.167
Median Benchmark	0.507	0.882	1.122	1.354	1.229	1.240	0.487	0.840	1.052	1.201	1.180	1.065
Median DESARIMA	0.408	0.729	0.990	1.231	1.155	1.044	0.370	0.667	0.903	1.134	1.090	0.968
GW core stat: Best	0.087	0.194	0.207	0.134	-0.017	0.032	0.099	0.266	0.298	0.078	0.043	0.180
t-Statistic	5.051	1.800	0.864	0.786	-0.106	0.334	4.257	2.028	1.184	0.886	0.479	1.975
GW core stat: Median	0.091	0.247	0.278	0.317	0.178	0.447	0.100	0.260	0.291	0.157	0.203	0.197
t-Statistic	5.461	2.126	1.247	1.556	0.826	1.490	4.629	2.352	1.278	1.626	1.329	2.102

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.2 Chile

Chile: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.554	1.326	2.412	4.573	8.818	15.202	0.536	1.237	2.163	3.719	4.783	5.273
2. AR(6)	0.489	1.181	2.094	3.481	4.104	3.514	0.474	1.083	1.800	2.731	2.608	2.589
3. AR(12)	0.545	1.467	2.657	4.243	5.239	4.686	0.468	1.146	1.936	2.932	2.844	2.676
4. ARMA(1,1)	0.481	1.247	2.196	3.731	4.822	4.729	0.471	1.157	2.002	3.228	3.435	3.237
5. AR(12) [BIC]	0.512	1.182	2.137	3.562	3.760	3.854	0.477	1.088	1.906	3.120	3.257	2.928
6. AR(12) [AIC]	0.502	1.246	2.175	3.585	3.726	3.759	0.466	1.112	1.886	2.879	2.680	2.794
7. ARMA(12,6) [BIC]	0.539	1.260	2.205	3.828	4.585	4.917	0.476	1.161	2.078	3.329	3.517	3.223
8. ARMA(12,6) [AIC]	0.556	1.325	2.292	3.972	4.411	4.580	0.499	1.170	1.982	3.250	3.275	3.316
9. CCR-F | M3	0.567	1.286	2.289	3.933	5.441	5.261	0.521	1.213	2.168	3.674	4.784	5.112
10. CCR-F | M4	0.698	1.764	3.533	7.706	23.600	8.998	0.604	1.433	2.528	4.327	6.449	6.835
11. Single ES	0.532	1.214	2.084	3.333	3.693	3.297	0.531	1.213	2.083	3.333	3.693	3.298
12. Double ES	0.547	1.290	2.570	5.823	11.579	11.643	0.516	1.235	2.489	5.727	11.454	11.475
13. Holt-Winters	0.641	1.504	2.944	5.478	10.663	9.773	0.554	1.322	2.588	5.226	9.844	8.748
1. DESARIMA 1	0.453	1.078	1.872	2.988	3.208	3.103	0.443	1.063	1.859	3.071	3.285	3.093
2. DESARIMA 2	0.393	0.980	1.705	2.765	2.943	2.942	0.412	1.081	1.933	3.296	3.582	3.777
3. DESARIMA 3	0.403	0.959	1.728	2.817	2.969	2.951	0.411	1.017	1.858	3.217	3.520	3.660
4. DESARIMA 4	0.392	0.957	1.685	2.819	3.022	2.997	0.396	0.985	1.721	2.755	2.931	2.959
5. DESARIMA 5	0.432	0.990	1.721	2.794	2.938	2.944	0.472	1.135	1.974	3.304	3.511	3.685
6. DESARIMA 6	0.531	1.213	2.083	3.333	3.693	3.298	0.531	1.213	2.083	3.333	3.693	3.298
7. DESARIMA 7	0.470	1.152	2.015	3.303	3.736	3.300	0.467	1.144	2.012	3.300	3.730	3.306
8. DESARIMA 8	0.397	0.931	1.651	2.730	2.992	2.947	0.404	1.021	1.868	3.211	3.564	3.744
9. DESARIMA 9	0.479	1.102	1.975	3.340	3.894	3.338	0.479	1.115	1.987	3.304	3.794	3.324
10. DESARIMA 10	0.477	1.159	2.134	3.497	4.008	3.326	0.463	1.160	2.036	3.308	3.720	3.317
Median Benchmark	0.483	1.127	2.038	3.613	4.509	4.586	0.463	1.070	1.864	3.202	3.407	3.206
Median DESARIMA	0.411	1.009	1.788	2.872	3.119	3.020	0.405	0.995	1.747	2.841	3.012	2.907
GW core stat: Best	0.078	0.529	1.617	3.660	5.007	2.219	0.060	0.201	0.277	-0.133	-1.790	-2.053
t-Statistic	3.558	2.347	2.018	1.899	1.948	1.254	2.515	1.016	0.479	-0.131	-1.229	-1.871
GW core stat: Median	0.064	0.251	0.958	4.810	10.605	11.908	0.051	0.154	0.423	2.182	2.531	1.825
t-Statistic	3.759	2.105	2.055	1.913	2.033	1.929	2.665	0.973	0.777	1.127	1.146	0.891

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.3 Colombia

Colombia: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.482	1.273	2.301	5.641	25.245	109.568	0.456	1.063	1.466	2.076	2.834	3.828
2. AR(6)	0.473	1.255	2.065	3.920	11.950	42.176	0.416	1.049	1.467	2.010	2.360	2.673
3. AR(12)	0.508	1.356	2.280	4.324	11.779	34.160	0.417	1.053	1.572	2.203	2.601	3.471
4. ARMA(1,1)	0.431	1.094	1.636	2.508	4.057	6.864	0.404	1.018	1.407	1.930	2.396	2.816
5. AR(12) [BIC]	0.444	1.216	1.864	2.571	3.271	3.639	0.408	1.055	1.501	2.060	2.648	2.886
6. AR(12) [AIC]	0.435	1.182	1.805	2.486	3.193	3.425	0.431	1.117	1.632	2.076	2.584	2.669
7. ARMA(12,6) [BIC]	0.485	1.210	1.802	2.526	3.181	3.632	0.435	1.136	1.600	2.154	2.606	2.938
8. ARMA(12,6) [AIC]	0.506	1.253	1.904	2.717	3.268	3.565	0.441	1.225	1.891	2.859	3.102	3.574
9. CCR-F | M3	0.464	1.177	1.721	2.618	4.076	5.322	0.433	1.091	1.577	2.291	3.472	4.455
10. CCR-F | M4	0.582	1.496	2.460	5.055	18.173	51.996	0.510	1.177	1.656	2.434	3.409	4.465
11. Single ES	0.461	1.071	1.479	2.023	2.598	2.820	0.461	1.071	1.478	2.023	2.597	2.821
12. Double ES	0.444	1.286	2.444	5.122	10.232	14.752	0.444	1.291	2.397	5.015	9.979	14.416
13. Holt-Winters	0.539	1.528	2.779	5.243	10.432	14.759	0.497	1.382	2.495	4.795	9.212	13.028
1. DESARIMA 1	0.383	0.955	1.451	2.260	2.854	3.235	0.368	0.984	1.618	2.696	3.327	3.823
2. DESARIMA 2	0.375	0.974	1.636	2.995	3.755	4.284	0.400	1.233	2.304	4.484	5.263	5.989
3. DESARIMA 3	0.341	0.873	1.455	2.592	3.516	4.019	0.364	1.116	2.269	4.850	6.465	7.229
4. DESARIMA 4	0.368	0.913	1.505	2.741	3.645	4.174	0.353	1.019	1.973	4.121	6.081	6.918
5. DESARIMA 5	0.426	1.043	1.698	3.046	3.736	4.276	0.459	1.181	2.045	3.768	4.490	5.245
6. DESARIMA 6	0.461	1.071	1.478	2.023	2.597	2.821	0.461	1.071	1.478	2.023	2.597	2.821
7. DESARIMA 7	0.417	0.996	1.417	1.988	2.559	2.772	0.403	1.019	1.437	2.003	2.573	2.793
8. DESARIMA 8	0.333	0.860	1.417	2.589	3.528	4.039	0.361	1.113	2.253	4.851	6.547	7.296
9. DESARIMA 9	0.392	1.011	1.446	2.069	2.590	2.715	0.397	1.013	1.438	2.030	2.566	2.771
10. DESARIMA 10	0.403	1.021	1.421	1.998	2.566	2.766	0.414	1.039	1.453	2.024	2.575	2.786
Median Benchmark	0.421	1.119	1.662	2.369	3.143	3.575	0.411	1.031	1.465	1.968	2.446	2.724
Median DESARIMA	0.363	0.938	1.428	2.354	3.134	3.582	0.362	0.977	1.624	2.901	3.813	4.444
GW core stat: Best	0.075	0.409	0.18	0.141	0.198	0.578	0.039	0.068	-0.083	-0.284	-1.014	-0.552
t-Statistic	2.245	1.293	0.451	0.902	0.865	0.734	1.211	0.481	-0.544	-0.538	-1.154	-0.501
GW core stat: Median	0.046	0.373	0.723	0.071	0.060	-0.050	0.038	0.108	-0.489	-4.543	-8.555	-12.327
t-Statistic	2.958	2.180	1.860	0.079	0.035	-0.019	2.450	0.747	-1.265	-2.426	-2.250	-2.217

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.4 Israel

Israel: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.646	1.458	2.289	3.231	3.657	2.833	0.644	1.477	2.390	3.600	3.876	2.481
2. AR(6)	0.585	1.447	2.259	3.265	3.612	3.445	0.555	1.411	2.357	3.624	3.643	2.974
3. AR(12)	0.637	1.563	2.530	3.711	4.257	4.112	0.552	1.376	2.379	3.719	3.591	2.329
4. ARMA(1,1)	0.580	1.397	2.230	3.043	3.265	2.669	0.560	1.409	2.302	3.441	3.521	2.553
5. AR(12) [BIC]	0.602	1.542	2.590	3.610	3.159	2.919	0.564	1.446	2.437	3.714	3.764	3.467
6. AR(12) [AIC]	0.596	1.555	2.660	4.152	4.175	4.610	0.566	1.436	2.409	3.643	3.623	2.870
7. ARMA(12,6) [BIC]	0.700	1.778	2.730	3.725	3.619	3.264	0.565	1.505	2.579	3.832	3.886	2.847
8. ARMA(12,6) [AIC]	0.689	1.784	2.686	3.889	4.268	5.167	0.619	1.567	2.532	3.814	3.463	2.743
9. CCR-F | M3	0.696	1.729	2.729	3.892	5.178	5.607	0.600	1.491	2.406	3.773	4.639	5.202
10. CCR-F | M4	0.878	2.120	3.656	7.175	17.847	53.115	0.705	1.614	2.619	3.884	4.169	3.937
11. Single ES	0.633	1.450	2.360	3.557	3.710	2.736	0.633	1.450	2.360	3.557	3.710	2.736
12. Double ES	0.633	1.756	3.400	7.078	14.008	21.413	0.637	1.806	3.502	7.408	14.997	23.037
13. Holt-Winters	0.805	2.078	3.785	6.882	12.982	19.085	0.670	1.882	3.544	6.961	13.966	21.288
1. DESARIMA 1	0.547	1.215	2.049	3.279	3.052	2.597	0.500	1.187	1.929	3.007	2.979	2.312
2. DESARIMA 2	0.472	1.169	1.951	3.183	3.146	2.576	0.457	1.261	2.271	4.167	4.288	4.104
3. DESARIMA 3	0.458	1.136	1.916	3.184	3.197	2.607	0.438	1.140	2.056	3.862	4.109	3.954
4. DESARIMA 4	0.458	1.143	1.917	3.161	3.173	2.592	0.438	1.163	2.122	3.966	4.226	4.008
5. DESARIMA 5	0.522	1.217	2.006	3.233	3.153	2.575	0.557	1.367	2.387	4.279	4.297	4.134
6. DESARIMA 6	0.633	1.450	2.360	3.557	3.710	2.736	0.633	1.450	2.360	3.557	3.710	2.736
7. DESARIMA 7	0.577	1.394	2.298	3.538	3.731	2.816	0.554	1.380	2.287	3.531	3.731	2.805
8. DESARIMA 8	0.452	1.134	1.891	3.093	3.139	2.574	0.436	1.133	2.042	3.837	4.189	3.958
9. DESARIMA 9	0.562	1.385	2.263	3.557	3.830	3.018	0.556	1.375	2.252	3.555	3.854	3.059
10. DESARIMA 10	0.573	1.398	2.290	3.586	3.807	2.901	0.552	1.377	2.278	3.531	3.774	2.911
Median Benchmark	0.572	1.405	2.292	3.399	3.329	2.751	0.552	1.382	2.267	3.457	3.471	2.392
Median DESARIMA	0.469	1.155	1.957	3.227	3.162	2.576	0.451	1.147	1.985	3.445	3.509	3.033
GW core stat: Best	0.133	0.667	1.396	-0.309	0.663	0.499	0.114	0.610	1.579	2.803	3.113	0.078
t-Statistic	3.543	2.241	1.800	-0.298	0.522	0.387	3.999	2.679	2.816	3.210	1.975	0.096
GW core stat: Median	0.107	0.639	1.423	1.144	1.081	0.929	0.101	0.596	1.196	0.080	-0.264	-3.477
t-Statistic	4.040	2.879	3.051	1.069	0.693	0.572	3.750	2.525	2.540	0.069	-0.133	-2.307

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.5 Mexico

Mexico: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.382	0.886	1.480	2.534	4.279	6.610	0.391	0.919	1.554	2.621	3.768	4.667
2. AR(6)	0.367	0.942	1.623	2.923	4.310	5.013	0.401	1.317	2.868	6.389	10.387	10.106
3. AR(12)	0.391	1.010	1.868	3.490	5.055	7.444	0.401	1.238	2.531	5.651	8.852	9.217
4. ARMA(1,1)	0.348	0.872	1.461	2.436	3.671	4.923	0.376	0.917	1.598	2.782	4.222	5.344
5. AR(12) [BIC]	0.366	0.935	1.633	2.884	3.920	4.467	0.376	1.133	2.501	5.715	8.737	8.742
6. AR(12) [AIC]	0.384	0.976	1.704	3.094	4.002	4.578	0.395	1.248	2.649	5.888	9.547	9.053
7. ARMA(12,6) [BIC]	0.387	1.048	1.783	3.141	4.249	4.689	0.383	1.177	2.421	5.162	8.603	8.952
8. ARMA(12,6) [AIC]	0.431	1.086	1.888	3.384	4.352	4.793	0.402	1.342	2.980	6.585	10.632	9.955
9. CCR-F | M3	0.445	1.133	1.652	2.115	3.648	6.256	0.379	0.985	1.652	2.966	4.696	7.053
10. CCR-F | M4	0.519	1.270	2.076	3.584	6.806	9.660	0.530	1.358	2.436	4.535	8.378	12.521
11. Single ES	0.390	0.918	1.549	2.593	3.645	4.310	0.388	0.916	1.545	2.589	3.640	4.305
12. Double ES	0.388	1.017	1.867	3.749	6.572	10.495	0.380	1.038	1.871	3.856	7.083	11.374
13. Holt-Winters	0.500	1.238	1.984	3.221	5.982	9.322	0.420	1.131	2.070	4.233	7.860	12.739
1. DESARIMA 1	0.336	0.899	1.739	2.997	4.075	4.746	0.315	0.818	1.464	2.593	3.652	4.316
2. DESARIMA 2	0.372	1.065	2.050	3.972	5.131	5.806	0.434	1.428	2.826	5.681	6.912	7.686
3. DESARIMA 3	0.325	0.886	1.685	3.080	4.318	4.962	0.354	1.070	2.177	4.212	6.576	7.453
4. DESARIMA 4	0.325	0.846	1.602	3.042	4.212	4.877	0.360	1.078	2.288	4.698	6.892	7.765
5. DESARIMA 5	0.448	1.164	2.076	3.694	4.775	5.456	0.630	1.673	3.072	5.959	6.994	7.782
6. DESARIMA 6	0.388	0.916	1.545	2.589	3.640	4.305	0.388	0.916	1.545	2.589	3.640	4.305
7. DESARIMA 7	0.340	0.869	1.484	2.533	3.567	4.238	0.355	0.867	1.478	2.527	3.557	4.228
8. DESARIMA 8	0.317	0.868	1.656	3.210	4.479	5.170	0.357	1.064	2.227	4.349	6.680	7.665
9. DESARIMA 9	0.339	0.841	1.357	2.380	3.265	3.972	0.343	0.863	1.375	2.389	3.115	3.813
10. DESARIMA 10	0.347	0.841	1.406	2.470	3.254	4.072	0.351	0.884	1.384	2.395	3.216	3.905
Median Benchmark	0.352	0.884	1.464	2.493	3.655	4.623	0.351	0.897	1.659	3.141	4.826	5.948
Median ESARIMA	0.311	0.839	1.540	2.752	3.883	4.559	0.311	0.865	1.677	3.191	4.732	5.523
GW core stat: Best	0.021	0.054	0.293	-1.190	2.698	2.798	0.042	0.170	0.497	0.992	3.548	3.994
t-Statistic	1.387	0.435	0.945	-0.538	1.813	1.648	2.330	1.839	0.798	0.855	1.384	1.357
GW core stat: Median	0.027	0.078	-0.228	-1.356	-1.714	0.585	0.026	0.056	-0.061	-0.317	0.898	4.874
t-Statistic	4.142	1.417	-0.853	-1.231	-0.862	0.136	2.589	0.570	-0.152	-0.330	0.557	2.468

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.6 Peru

Peru: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.471	1.100	1.886	3.232	4.677	6.165	0.449	1.006	1.649	2.552	2.961	2.782
2. AR(6)	0.426	0.998	1.706	2.694	3.130	3.554	0.415	0.921	1.503	2.402	3.221	3.888
3. AR(12)	0.447	1.075	1.904	2.872	3.439	4.278	0.422	0.949	1.572	2.517	3.686	5.704
4. ARMA(1,1)	0.440	1.062	1.804	2.994	3.946	4.438	0.421	0.975	1.582	2.398	2.667	2.378
5. AR(12) [BIC]	0.439	1.052	1.739	2.718	3.054	2.504	0.821	1.156	1.673	2.407	2.686	2.843
6. AR(12) [AIC]	0.474	1.144	1.990	2.847	2.855	2.339	0.817	1.142	1.594	2.267	2.619	2.780
7. ARMA(12,6) [BIC]	0.514	1.260	1.932	2.941	3.319	2.977	0.451	0.989	1.601	2.499	2.707	2.843
8. ARMA(12,6) [AIC]	0.513	1.270	2.077	3.079	3.453	3.169	0.466	0.979	1.572	2.434	2.955	3.373
9. CCR-F | M3	0.507	1.146	1.919	3.074	4.056	4.388	0.442	1.022	1.707	2.825	3.894	4.585
10. CCR-F | M4	0.599	1.451	2.588	4.878	11.623	8.879	0.502	1.141	1.881	2.973	3.867	4.480
11. Single ES	0.448	1.001	1.632	2.528	2.905	2.417	0.448	1.001	1.632	2.528	2.905	2.417
12. Double ES	0.450	1.098	2.123	4.731	9.302	11.995	0.449	1.099	2.124	4.719	9.239	11.965
13. Holt-Winters	0.541	1.262	2.270	3.923	6.967	6.873	0.475	1.076	1.889	3.533	6.167	6.386
1. DESARIMA 1	0.374	0.841	1.424	2.393	2.729	2.787	0.372	0.909	1.575	2.803	3.249	3.210
2. DESARIMA 2	0.342	0.817	1.381	2.338	2.734	2.738	0.362	0.949	1.721	3.154	3.482	3.463
3. DESARIMA 3	0.334	0.803	1.357	2.285	2.698	2.717	0.354	0.911	1.598	2.508	2.966	2.808
4. DESARIMA 4	0.337	0.826	1.473	2.959	7.607	26.491	0.325	0.804	1.476	2.967	6.831	19.456
5. DESARIMA 5	0.368	0.842	1.409	2.355	2.731	2.774	0.388	0.923	1.616	2.897	3.277	3.154
6. DESARIMA 6	0.448	1.001	1.632	2.528	2.905	2.417	0.448	1.001	1.632	2.528	2.905	2.417
7. DESARIMA 7	0.421	0.972	1.599	2.521	2.918	2.437	0.419	0.972	1.600	2.522	2.919	2.433
8. DESARIMA 8	0.332	0.791	1.329	2.276	2.705	2.686	0.335	0.844	1.537	2.894	3.368	3.344
9. DESARIMA 9	0.411	0.945	1.557	2.523	2.971	2.486	0.409	0.949	1.573	2.521	2.946	2.452
10. DESARIMA 10	0.425	0.959	1.589	2.667	3.245	2.727	0.413	0.940	1.571	2.559	3.021	2.487
Median Benchmark	0.432	1.042	1.727	2.780	3.379	2.992	0.418	0.941	1.524	2.410	2.749	2.696
Median DESARIMA	0.352	0.820	1.365	2.259	2.653	2.466	0.345	0.813	1.387	2.229	2.580	2.400
GW core stat: Best	0.071	0.370	0.896	1.214	0.874	-0.372	0.067	0.202	0.080	-1.150	-1.577	-0.186
t-Statistic	5.692	3.585	2.316	1.208	0.461	-0.267	4.126	2.396	0.246	-0.898	-0.918	-0.146
GW core stat: Median	0.062	0.413	1.119	2.624	4.378	2.870	0.056	0.224	0.398	0.840	0.900	1.507
t-Statistic	5.649	4.299	3.564	2.167	1.770	0.962	4.811	3.240	1.597	0.933	0.489	0.537

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.7 South Africa

South Africa: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.743	1.867	3.398	5.884	10.076	19.519	0.681	1.602	2.728	3.999	4.334	5.029
2. AR(6)	0.655	1.595	2.922	5.263	8.917	17.699	0.605	1.439	2.567	3.949	3.338	3.704
3. AR(12)	0.761	1.903	3.603	7.896	23.826	19.912	0.625	1.379	2.378	3.799	3.494	3.627
4. ARMA(1,1)	0.666	1.740	3.095	4.855	6.924	11.008	0.619	1.528	2.600	3.698	3.834	4.282
5. AR(12) [BIC]	1.469	1.965	2.854	4.027	4.157	4.353	0.606	1.433	2.454	3.625	3.522	3.663
6. AR(12) [AIC]	1.468	1.998	2.937	4.233	4.138	4.382	0.618	1.422	2.494	3.840	3.334	3.563
7. ARMA(12,6) [BIC]	0.707	1.741	3.001	4.850	5.862	6.952	0.651	1.489	2.557	3.820	3.474	3.554
8. ARMA(12,6) [AIC]	0.678	1.758	3.087	4.984	6.067	7.379	0.624	1.421	2.411	3.642	3.598	3.380
9. CCR-F | M3	0.740	1.846	3.357	5.322	7.349	10.061	0.644	1.551	2.766	4.533	5.599	7.247
10. CCR-F | M4	0.855	2.143	3.990	7.228	15.094	29.816	0.740	1.747	3.012	4.720	6.116	7.701
11. Single ES	0.678	1.599	2.770	4.195	4.643	5.551	0.678	1.599	2.770	4.195	4.643	5.551
12. Double ES	0.646	1.588	3.247	7.622	14.176	21.754	0.630	1.607	3.291	7.772	14.722	22.655
13. Holt-Winters	0.854	2.244	4.527	8.619	15.279	23.896	0.678	1.745	3.556	7.684	14.103	21.892
1. DESARIMA 1	0.537	1.239	2.218	3.655	3.961	4.146	0.497	1.166	2.065	3.470	3.661	3.702
2. DESARIMA 2	0.505	1.209	2.137	3.551	3.691	3.914	0.463	1.125	2.015	3.372	3.514	3.684
3. DESARIMA 3	0.487	1.171	2.127	3.615	4.285	4.117	0.441	1.053	1.910	3.295	3.608	3.744
4. DESARIMA 4	0.488	1.187	2.211	4.437	11.241	45.161	0.434	0.985	1.768	3.170	3.514	3.744
5. DESARIMA 5	0.541	1.252	2.198	3.598	3.732	3.945	0.497	1.169	2.061	3.401	3.516	3.674
6. DESARIMA 6	0.678	1.599	2.770	4.195	4.643	5.551	0.678	1.599	2.770	4.195	4.643	5.551
7. DESARIMA 7	0.621	1.514	2.680	4.173	4.654	5.570	0.616	1.527	2.696	4.176	4.648	5.566
8. DESARIMA 8	0.485	1.142	2.026	3.485	3.718	3.942	0.446	1.056	1.916	3.300	3.508	3.693
9. DESARIMA 9	0.605	1.454	2.592	4.223	4.716	5.656	0.602	1.457	2.594	4.186	4.703	5.641
10. DESARIMA 10	0.604	1.442	2.661	4.609	5.301	6.402	0.604	1.449	2.585	4.326	4.888	5.906
Median Benchmark	0.635	1.533	2.748	4.439	5.922	7.077	0.600	1.353	2.339	3.548	3.739	4.115
Median DESARIMA	0.510	1.198	2.147	3.620	3.986	4.364	0.470	1.113	1.996	3.284	3.607	3.784
GW core stat: Best	0.182	1.220	3.564	4.075	3.496	3.634	0.178	0.931	2.531	3.089	-1.190	-2.068
t-Statistic	4.169	2.580	2.858	1.093	1.771	1.404	3.615	3.118	2.212	1.562	-1.686	-1.732
GW core stat: Median	0.144	0.916	2.938	6.605	19.188	31.047	0.139	0.593	1.486	1.802	0.976	2.622
t-Statistic	3.543	3.048	3.085	2.094	2.502	2.309	3.539	2.427	2.767	1.678	0.901	1.477

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.8 Sweden

Sweden: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.417	0.853	1.379	2.182	2.900	2.841	0.398	0.762	1.147	1.601	1.660	1.357
2. AR(6)	0.462	0.945	1.522	2.392	3.466	5.124	0.414	0.755	1.110	1.499	1.448	1.265
3. AR(12)	0.522	1.144	2.091	4.019	4.977	18.620	0.430	0.784	1.171	1.511	1.342	1.338
4. ARMA(1,1)	0.426	0.844	1.343	2.170	3.165	4.198	0.405	0.754	1.120	1.537	1.549	1.318
5. AR(12) [BIC]	0.615	0.954	1.298	1.824	2.166	2.012	0.416	0.768	1.165	1.599	1.657	1.399
6. AR(12) [AIC]	0.629	0.988	1.327	1.870	2.145	2.220	0.423	0.780	1.155	1.531	1.552	1.354
7. ARMA(12,6) [BIC]	0.512	1.030	1.502	2.070	2.537	2.900	0.427	0.820	1.238	1.704	1.660	1.662
8. ARMA(12,6) [AIC]	0.528	1.052	1.535	2.041	2.525	3.034	0.442	0.816	1.268	1.659	1.560	1.784
9. CCR-F | M3	0.510	0.943	1.424	2.159	3.204	3.396	0.431	0.820	1.260	1.915	2.640	2.666
10. CCR-F | M4	0.519	1.021	1.734	3.317	10.614	40.781	0.440	0.879	1.390	2.075	2.625	2.596
11. Single ES	0.405	0.764	1.168	1.741	2.082	1.858	0.400	0.762	1.168	1.742	2.088	1.863
12. Double ES	0.453	0.980	1.782	3.663	7.014	8.885	0.444	0.933	1.688	3.412	6.279	7.560
13. Holt-Winters	0.541	1.158	2.065	3.802	7.543	8.883	0.441	0.882	1.437	2.294	3.551	3.590
1. DESARIMA 1	0.341	0.615	0.937	1.422	1.581	1.459	0.319	0.578	0.878	1.292	1.411	1.398
2. DESARIMA 2	0.338	0.616	0.964	1.481	1.591	1.438	0.322	0.579	0.879	1.299	1.351	1.319
3. DESARIMA 3	0.352	0.647	0.976	1.536	1.660	1.481	0.327	0.569	0.868	1.294	1.380	1.391
4. DESARIMA 4	0.359	0.681	1.099	2.333	12.529	79.961	0.329	0.605	0.918	1.367	1.383	1.323
5. DESARIMA 5	0.326	0.610	0.959	1.477	1.582	1.440	0.318	0.579	0.877	1.300	1.347	1.315
6. DESARIMA 6	0.400	0.762	1.168	1.742	2.088	1.863	0.400	0.762	1.168	1.742	2.088	1.863
7. DESARIMA 7	0.411	0.764	1.161	1.739	2.087	1.864	0.410	0.763	1.165	1.745	2.093	1.872
8. DESARIMA 8	0.347	0.635	0.982	1.505	1.609	1.447	0.325	0.579	0.879	1.297	1.352	1.319
9. DESARIMA 9	0.418	0.774	1.162	1.770	2.148	1.921	0.406	0.760	1.162	1.744	2.095	1.873
10. DESARIMA 10	0.424	0.781	1.170	1.764	2.125	1.840	0.412	0.773	1.182	1.758	2.078	1.860
Median Benchmark	0.428	0.843	1.291	1.967	2.513	2.436	0.402	0.768	1.156	1.619	1.674	1.420
Median DESARIMA	0.343	0.629	0.974	1.506	1.670	1.499	0.319	0.573	0.876	1.285	1.409	1.409
GW core stat: Best	0.058	0.212	0.487	1.010	1.835	1.385	0.057	0.245	0.478	0.578	-0.014	-0.130
t-Statistic	2.717	2.160	2.119	1.672	3.020	4.429	2.361	2.559	2.451	1.091	-0.119	-1.031
GW core stat: Median	0.065	0.316	0.717	1.601	3.528	3.687	0.060	0.262	0.571	0.970	0.818	0.029
t-Statistic	2.848	2.507	2.322	1.822	3.204	3.224	2.787	2.594	2.489	1.786	2.508	0.176

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.9 Switzerland

Switzerland: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.345	0.655	0.962	1.240	1.366	1.854	0.338	0.623	0.847	0.966	0.870	0.895
2. AR(6)	0.357	0.663	0.914	1.073	1.000	1.079	0.336	0.630	0.842	0.985	0.869	0.899
3. AR(12)	0.389	0.759	1.084	1.403	2.560	3.530	0.344	0.669	0.891	1.001	1.198	1.045
4. ARMA(1,1)	0.350	0.662	0.954	1.180	1.196	1.412	0.340	0.625	0.846	0.959	0.871	0.894
5. AR(12) [BIC]	0.354	0.643	0.943	1.248	1.091	1.147	0.347	0.632	0.848	0.962	0.867	0.892
6. AR(12) [AIC]	0.361	0.672	0.971	1.277	1.099	1.170	0.352	0.683	0.941	1.051	0.866	0.927
7. ARMA(12,6) [BIC]	0.409	0.748	0.990	1.198	1.150	1.202	0.348	0.656	0.900	1.157	0.992	0.954
8. ARMA(12,6) [AIC]	0.427	0.751	1.015	1.205	1.131	1.298	0.330	0.612	0.840	1.032	0.927	0.925
9. CCR-F | M3	0.394	0.729	1.090	1.543	1.592	1.717	0.368	0.692	1.013	1.415	1.266	1.450
10. CCR-F | M4	0.408	0.803	1.293	1.965	3.051	4.430	0.367	0.690	0.971	1.174	1.113	1.241
11. Single ES	0.340	0.642	0.942	1.312	1.097	1.167	0.342	0.646	0.944	1.313	1.097	1.168
12. Double ES	0.374	0.736	1.316	2.732	4.292	5.059	0.373	0.775	1.371	2.784	4.387	5.190
13. Holt-Winters	0.403	0.817	1.451	2.410	3.414	2.980	0.372	0.714	1.081	1.495	1.392	1.390
1. DESARIMA 1	0.303	0.563	0.753	0.997	0.856	0.935	0.295	0.531	0.701	0.947	0.903	0.927
2. DESARIMA 2	0.306	0.556	0.752	1.005	0.861	0.940	0.304	0.555	0.709	0.929	0.885	0.951
3. DESARIMA 3	0.322	0.579	0.762	1.017	0.846	0.951	0.295	0.531	0.701	0.973	0.924	0.959
4. DESARIMA 4	0.315	0.561	0.788	1.038	1.811	14.674	0.301	0.549	0.700	0.878	0.863	0.941
5. DESARIMA 5	0.303	0.562	0.762	0.998	0.858	0.933	0.301	0.553	0.707	0.934	0.890	0.951
6. DESARIMA 6	0.342	0.646	0.944	1.313	1.097	1.168	0.342	0.646	0.944	1.313	1.097	1.168
7. DESARIMA 7	0.343	0.638	0.933	1.314	1.102	1.166	0.343	0.645	0.943	1.314	1.099	1.169
8. DESARIMA 8	0.307	0.556	0.753	1.007	0.865	0.940	0.305	0.557	0.708	0.924	0.886	0.957
9. DESARIMA 9	0.342	0.635	0.934	1.323	1.111	1.166	0.343	0.645	0.943	1.315	1.101	1.170
10. DESARIMA 10	0.347	0.647	0.973	1.359	1.913	14.867	0.347	0.659	0.962	1.256	1.112	1.137
Median Benchmark	0.347	0.645	0.953	1.213	1.153	1.259	0.340	0.629	0.859	0.999	0.870	0.961
Median DESARIMA	0.306	0.555	0.762	1.025	0.859	0.956	0.296	0.535	0.717	0.962	0.890	0.947
GW core stat: Best	0.024	0.103	0.269	0.158	0.284	0.293	0.022	0.093	0.215	0.150	0.006	-0.063
t-Statistic	2.406	1.755	2.021	1.010	1.938	1.322	1.793	1.665	1.515	1.601	0.090	-0.950
GW core stat: Median	0.027	0.108	0.327	0.420	0.591	0.671	0.028	0.109	0.224	0.073	-0.036	0.026
t-Statistic	3.230	2.420	2.596	1.807	2.862	2.437	3.064	2.584	2.455	0.951	-0.689	0.290

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.10 Turkey

Turkey: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	2.307	5.907	10.212	17.249	22.177	34.618	2.431	6.198	10.542	17.214	26.659	38.221
2. AR(6)	2.047	6.657	13.565	25.144	23.461	33.715	2.124	6.384	11.311	18.786	28.554	37.548
3. AR(12)	2.162	6.468	13.207	27.025	26.267	50.816	2.292	7.166	13.180	23.750	34.691	41.805
4. ARMA(1,1)	1.995	5.729	9.977	16.491	19.662	25.761	2.150	6.270	11.008	18.175	28.230	38.363
5. AR(12) [BIC]	1.997	6.201	12.127	21.406	22.742	29.559	2.040	5.906	10.910	18.385	27.013	35.681
6. AR(12) [AIC]	1.945	6.073	11.888	21.175	22.586	29.863	2.036	6.235	11.719	19.948	27.534	36.272
7. ARMA(12,6) [BIC]	2.038	6.152	11.666	20.086	21.489	29.083	2.080	6.603	11.131	18.858	26.878	35.339
8. ARMA(12,6) [AIC]	2.355	7.066	12.381	20.631	20.948	30.434	2.153	7.238	12.275	21.421	27.796	36.243
9. CCR-F | M3	2.167	6.319	11.001	16.817	20.428	28.317	2.015	5.590	9.456	14.651	19.642	27.877
10. CCR-F | M4	2.800	7.507	13.387	22.583	40.012	65.864	2.480	6.084	9.829	14.442	18.162	25.815
11. Single ES	2.288	5.713	9.442	14.319	18.092	24.271	2.290	5.714	9.443	14.319	18.095	24.270
12. Double ES	2.104	6.641	13.415	30.070	53.270	85.556	2.094	6.379	12.906	29.052	50.334	80.809
13. Holt-Winters	2.649	8.200	16.406	32.217	56.980	91.070	2.377	5.984	10.248	15.380	23.992	38.161
1. DESARIMA 1	1.804	4.947	9.056	16.875	22.184	28.924	2.021	5.129	9.067	16.723	23.558	31.223
2. DESARIMA 2	1.650	4.894	9.010	17.471	23.810	30.721	2.153	6.634	12.816	26.022	32.989	39.558
3. DESARIMA 3	1.501	4.547	8.819	18.351	24.506	30.595	1.884	5.492	10.660	22.543	32.100	39.209
4. DESARIMA 4	1.467	4.480	8.801	18.840	23.667	31.246	1.889	5.261	9.849	20.994	31.203	38.500
5. DESARIMA 5	2.085	5.441	9.594	18.811	25.033	31.754	2.463	6.481	11.857	23.318	30.239	37.137
6. DESARIMA 6	2.290	5.714	9.443	14.319	18.095	24.270	2.290	5.714	9.443	14.319	18.095	24.270
7. DESARIMA 7	1.909	5.369	9.165	14.271	17.923	24.162	1.963	5.441	9.230	14.279	17.976	24.192
8. DESARIMA 8	1.449	4.237	7.919	15.940	22.433	29.517	1.860	5.250	10.038	21.797	32.018	38.968
9. DESARIMA 9	1.791	5.207	9.002	14.917	17.936	24.316	1.911	5.295	9.103	14.316	17.867	24.149
10. DESARIMA 10	1.832	5.361	9.503	16.515	18.346	24.449	1.938	5.374	9.170	14.274	17.899	24.161
Median Benchmark	1.943	5.553	9.531	16.647	18.532	25.815	2.056	5.861	10.112	17.020	25.534	34.797
Median DESARIMA	1.585	4.546	8.309	15.891	21.107	27.704	1.870	5.236	9.270	17.716	25.487	32.878
GW core stat: Best	1.681	14.686	26.429	1.363	6.100	5.252	0.600	4.945	6.970	1.312	8.196	5.861
t-Statistic	3.225	2.059	1.670	0.283	0.737	0.492	0.644	0.620	0.358	0.256	0.667	0.377
GW core stat: Median	1.265	10.163	21.801	24.600	-102.085	-101.073	0.727	6.932	16.330	-24.167	2.386	129.842
t-Statistic	2.328	1.965	1.629	0.522	-1.996	-1.201	1.153	1.469	1.417	-0.884	0.052	2.123

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.11 United Kingdom

United Kingdom: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.311	0.649	1.022	1.780	5.010	17.873	0.311	0.619	0.922	1.249	1.395	1.481
2. AR(6)	0.327	0.679	0.948	1.040	1.201	1.266	0.317	0.635	0.949	1.246	1.279	1.308
3. AR(12)	0.362	0.747	1.041	1.143	1.519	1.630	0.329	0.678	1.032	1.337	1.352	1.365
4. ARMA(1,1)	0.310	0.638	0.962	1.524	3.283	9.519	0.308	0.613	0.919	1.254	1.358	1.401
5. AR(12) [BIC]	0.307	0.607	0.825	0.950	1.002	1.162	0.372	0.604	0.914	1.176	1.242	1.274
6. AR(12) [AIC]	0.306	0.613	0.822	0.942	0.978	1.185	0.378	0.613	0.912	1.184	1.257	1.304
7. ARMA(12,6) [BIC]	0.329	0.716	0.971	1.042	1.051	1.330	0.315	0.639	0.949	1.234	1.298	1.279
8. ARMA(12,6) [AIC]	0.368	0.761	1.037	1.118	1.147	1.356	0.334	0.717	1.013	1.205	1.133	1.254
9. CCR-F | M3	0.344	0.65	0.942	1.216	1.364	1.199	0.318	0.609	0.892	1.167	1.371	1.542
10. CCR-F | M4	0.363	0.738	1.119	1.670	3.217	6.572	0.324	0.616	0.831	0.972	1.132	1.316
11. Single ES	0.303	0.576	0.845	1.087	1.094	0.995	0.303	0.579	0.849	1.088	1.097	0.995
12. Double ES	0.335	0.725	1.335	2.588	4.211	4.882	0.334	0.740	1.330	2.514	4.022	4.584
13. Holt-Winters	0.363	0.785	1.414	2.387	4.042	3.958	0.327	0.617	0.933	1.159	1.244	1.446
1. DESARIMA 1	0.265	0.489	0.715	0.944	1.030	1.144	0.264	0.502	0.766	1.140	1.200	1.301
2. DESARIMA 2	0.259	0.485	0.711	0.960	1.035	1.152	0.262	0.497	0.767	1.139	1.215	1.320
3. DESARIMA 3	0.266	0.493	0.729	1.014	1.071	1.149	0.267	0.511	0.782	1.157	1.216	1.337
4. DESARIMA 4	0.261	0.513	0.794	1.139	1.185	1.330	0.266	0.524	0.821	1.237	1.278	1.319
5. DESARIMA 5	0.261	0.487	0.713	0.960	1.036	1.151	0.263	0.499	0.768	1.140	1.213	1.310
6. DESARIMA 6	0.303	0.579	0.849	1.088	1.097	0.995	0.303	0.579	0.849	1.088	1.097	0.995
7. DESARIMA 7	0.300	0.572	0.841	1.092	1.097	0.997	0.302	0.579	0.848	1.089	1.100	0.997
8. DESARIMA 8	0.261	0.491	0.719	0.968	1.037	1.151	0.262	0.496	0.765	1.135	1.214	1.319
9. DESARIMA 9	0.300	0.578	0.848	1.107	1.113	1.005	0.303	0.579	0.848	1.092	1.101	0.998
10. DESARIMA 10	0.307	0.616	0.940	1.283	1.300	1.147	0.304	0.590	0.868	1.109	1.172	1.041
Median Benchmark	0.307	0.625	0.862	1.082	1.064	1.125	0.310	0.615	0.915	1.192	1.216	1.190
Median DESARIMA	0.262	0.492	0.727	0.984	1.039	1.120	0.262	0.503	0.768	1.142	1.175	1.246
GW core stat: Best	0.025	0.096	0.170	-0.003	-0.104	0.001	0.023	0.090	0.105	-0.238	0.000	0.000
t-Statistic	2.681	2.079	1.845	-0.052	-0.990	0.162	1.901	1.522	0.663	-1.794	0.000	0.000
GW core stat: Median	0.026	0.148	0.214	0.203	0.054	0.012	0.028	0.125	0.248	0.118	0.098	-0.138
t-Statistic	3.590	2.453	2.369	1.159	0.378	0.078	2.699	2.361	1.967	0.413	0.530	-1.021

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

B.12 United States

United States: Multi-horizon RMSPE estimates

	Rolling-window size: 40						Rolling-window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
1. AR(1)	0.534	1.101	1.553	1.855	2.119	1.604	0.519	1.064	1.425	1.634	1.619	1.519
2. AR(6)	0.508	1.265	1.821	1.837	1.956	1.715	0.474	1.113	1.488	1.614	1.516	1.512
3. AR(12)	0.550	1.454	2.442	3.499	6.828	2.585	0.483	1.214	1.744	2.040	2.259	1.646
4. ARMA(1,1)	0.483	1.083	1.503	1.723	1.838	1.690	0.465	1.028	1.350	1.490	1.516	1.492
5. AR(12) [BIC]	0.491	1.174	1.605	1.686	1.696	1.685	0.469	1.080	1.443	1.615	1.504	1.593
6. AR(12) [AIC]	0.498	1.180	1.600	1.802	1.721	1.788	0.477	1.142	1.483	1.490	1.616	1.620
7. ARMA(12,6) [BIC]	0.567	1.245	1.599	1.820	1.860	2.001	0.519	1.080	1.383	1.549	1.438	1.581
8. ARMA(12,6) [AIC]	0.557	1.268	1.783	2.005	2.195	2.425	0.442	1.003	1.542	1.722	1.688	1.654
9. CCR-F | M3	0.561	1.290	1.869	2.589	2.992	2.640	0.511	1.159	1.653	2.313	2.412	2.219
10. CCR-F | M4	0.633	1.345	1.997	2.714	3.941	4.216	0.560	1.170	1.631	1.964	2.052	1.819
11. Single ES	0.522	1.106	1.557	2.126	2.049	1.841	0.521	1.104	1.555	2.125	2.050	1.842
12. Double ES	0.645	1.566	2.765	5.548	9.616	12.643	0.584	1.492	2.674	5.487	9.572	12.113
13. Holt-Winters	0.640	1.467	2.462	3.945	6.100	5.651	0.561	1.206	1.768	2.437	2.987	2.317
1. DESARIMA 1	0.402	0.844	1.236	1.654	1.577	1.522	0.368	0.779	1.158	1.532	1.505	1.491
2. DESARIMA 2	0.373	0.842	1.213	1.652	1.569	1.578	0.331	0.753	1.103	1.501	1.474	1.499
3. DESARIMA 3	0.375	0.861	1.242	1.709	1.604	1.595	0.334	0.759	1.129	1.545	1.473	1.487
4. DESARIMA 4	0.371	0.841	1.208	1.665	1.562	1.568	0.331	0.751	1.099	1.504	1.471	1.493
5. DESARIMA 5	0.403	0.843	1.212	1.637	1.564	1.576	0.361	0.765	1.106	1.495	1.473	1.498
6. DESARIMA 6	0.521	1.104	1.555	2.125	2.050	1.842	0.521	1.104	1.555	2.125	2.050	1.842
7. DESARIMA 7	0.476	1.097	1.559	2.148	2.087	1.856	0.474	1.091	1.555	2.145	2.083	1.858
8. DESARIMA 8	0.374	0.855	1.224	1.696	1.570	1.581	0.334	0.755	1.108	1.521	1.475	1.502
9. DESARIMA 9	0.487	1.114	1.577	2.211	2.112	1.898	0.483	1.092	1.557	2.177	2.085	1.883
10. DESARIMA 10	0.487	1.103	1.557	2.160	2.074	1.867	0.483	1.086	1.544	2.141	2.050	1.861
Median Benchmark	0.485	1.084	1.521	1.810	2.047	1.866	0.457	1.041	1.378	1.713	1.544	1.615
Median DESARIMA	0.391	0.866	1.244	1.713	1.591	1.583	0.354	0.774	1.140	1.553	1.492	1.490
GW core stat: Best	0.095	0.466	0.799	0.160	0.435	0.258	0.086	0.442	0.615	-0.016	-0.097	0.013
t-Statistic	4.389	2.659	1.722	0.697	2.128	1.950	3.184	1.994	1.707	-0.061	-0.649	0.224
GW core stat: Median	0.082	0.425	0.764	0.343	1.657	0.977	0.084	0.485	0.599	0.524	0.158	0.388
t-Statistic	4.268	2.532	1.997	1.429	1.640	1.850	3.703	3.027	2.288	3.125	1.120	2.175

See tables 1 and 2 for DESARIMA and benchmark and specifications. Source: Authors' computations.

C Multi-horizon RMSPE estimates

Multi-horizon RMSPE estimates for R=40 and R=100

	Rolling window size: 40						Rolling window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
Canada												
Best benchmark	AR(1)	AR(1)	ARMA(1,1)	AR [BIC]	ARMA(1,1)	AR(1)	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(6)	AR [BIC]	AR(12)
RMSPE	0.493	0.843	1.080	1.263	1.108	1.060	0.482	0.836	1.044	1.140	1.087	1.047
Best DESARIMA	[1]	[1]	[1]	[2]	[1]	[2]	[5]	[5]	[5]	[5]	[1]	[2]
RMSPE	0.394***	0.719**	0.979	1.208	1.108	1.045	0.366***	0.658**	0.890	1.105	1.068	0.957**
Chile												
Best benchmark	ARMA(1,1)	AR(6)	ES [Single]	ES [Single]	ES [Single]	ES [Single]	AR [AIC]	AR(6)	AR(6)	AR(6)	AR(6)	AR(6)
RMSPE	0.481	1.181	2.084	3.333	3.693	3.297	0.466	1.083	1.800	2.731	2.608	2.589
Best DESARIMA	[4]	[8]	[8]	[8]	[5]	[2]	[4]	[4]	[4]	[4]	[4]	[4]
RMSPE	0.392***	0.931**	1.695**	2.730**	2.938**	2.942	0.396***	0.985	1.721	2.755	2.931	2.959
Colombia												
Best benchmark	ARMA(1,1)	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR(6)	AR [AIC]
RMSPE	0.431	1.071	1.479	2.023	2.593	2.820	0.404	1.018	1.407	1.930	2.360	2.669
Best DESARIMA	[8]	[8]	[8]	[7]	[7]	[9]	[4]	[1]	[7]	[7]	[9]	[9]
RMSPE	0.333**	0.860*	1.417	1.988	2.559	2.715	0.353	0.984	1.437	2.003	2.566	2.771
Israel												
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR [BIC]	ARMA(1,1)	AR(12)	AR(12)	ARMA(1,1)	ARMA(1,1)	ARMA [AIC]	AR(12)
RMSPE	0.580	1.397	2.230	3.043	3.159	2.669	0.552	1.376	2.302	3.441	3.463	2.329
Best DESARIMA	[8]	[8]	[8]	[8]	[1]	[8]	[8]	[8]	[1]	[1]	[1]	[1]
RMSPE	0.452***	1.134**	1.891**	3.093	3.052	2.574	0.436***	1.133***	1.929***	3.007***	2.979**	2.312

See tables 1 and 2 for DESARIMA and benchmark and specifications. GW test: * p<10%, ** p<5%, *** p<1%. Source: Authors' computations.

Multi-horizon RMSPE estimates for R=40 and R=100

	Rolling window size: 40						Rolling window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
Mexico												
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	CCR-F | M3	ES [Single]	ES [Single]	AR [BIC]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ES [Single]
RMSPE	0.348	0.872	1.461	2.115	3.645	4.310	0.376	0.916	1.545	2.589	3.640	4.305
Best DESARIMA	[8]	[10]	[9]	[9]	[10]	[9]	[1]	[1]	[9]	[9]	[9]	[9]
RMSPE	0.317*	0.841	1.357	2.380	3.254**	3.972*	0.315**	0.818**	1.375	2.389	3.115*	3.813*
Peru												
Best benchmark	AR(6)	AR(6)	ES [Single]	ES [Single]	AR [AIC]	AR [AIC]	AR(6)	AR(6)	AR(6)	AR [AIC]	AR [AIC]	ARMA(1,1)
RMSPE	0.426	0.998	1.632	2.528	2.855	2.339	0.415	0.921	1.503	2.267	2.619	2.378
Best DESARIMA	[8]	[8]	[8]	[8]	[3]	[6]	[4]	[4]	[4]	[3]	[6]	[6]
RMSPE	0.332***	0.791***	1.329**	2.276	2.698	2.417	0.325***	0.804***	1.476	2.508	2.905	2.417
South Africa												
Best benchmark	ES [Double]	ES [Double]	ES [Single]	AR [BIC]	AR [AIC]	AR [BIC]	AR(6)	AR(12)	AR(12)	AR [BIC]	AR [AIC]	ARMA [AIC]
RMSPE	0.646	1.588	2.770	4.027	4.138	4.353	0.605	1.379	2.378	3.625	3.334	3.380
Best DESARIMA	[8]	[8]	[8]	[8]	[2]	[2]	[4]	[4]	[4]	[4]	[8]	[5]
RMSPE	0.485***	1.142***	2.026***	3.485	3.691**	3.914*	0.434***	0.985***	1.768**	3.170*	3.508	3.674
Sweden												
Best benchmark	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	AR(1)	ARMA(1,1)	AR(6)	AR(6)	AR(12)	AR(6)
RMSPE	0.405	0.764	1.168	1.741	2.082	1.858	0.398	0.754	1.110	1.499	1.342	1.265
Best DESARIMA	[5]	[5]	[1]	[1]	[1]	[2]	[5]	[3]	[3]	[1]	[5]	[5]
RMSPE	0.326***	0.610**	0.937**	1.422**	1.581***	1.438***	0.318**	0.569***	0.868***	1.292	1.347	1.315

See tables 1 and 2 for DESARIMA and benchmark and specifications. GW test: * p<10%, ** p<5%, *** p<1%. Source: Authors' computations.

Multi-horizon RMSPE estimates for R=40 and R=100 (cont.)

	Rolling window size: 40						Rolling window size: 100					
	h=1	h=3	h=6	h=12	h=24	h=36	h=1	h=3	h=6	h=12	h=24	h=36
Switzerland												
Best benchmark	ES [Single]	ES [Single]	AR(6)	AR(6)	AR(6)	AR(6)	ARMA [AIC]	ARMA [AIC]	ARMA [AIC]	ARMA(1,1)	AR [AIC]	AR [BIC]
RMSPE	0.340	0.642	0.914	1.073	1.000	1.079	0.330	0.612	0.840	0.959	0.866	0.892
Best DESARIMA	[5]	[8]	[2]	[1]	[3]	[5]	[3]	[1]	[4]	[4]	[4]	[1]
RMSPE	0.303***	0.556**	0.752**	0.997	0.846**	0.933*	0.295**	0.531**	0.700*	0.878*	0.863	0.927
Turkey												
Best benchmark	AR [AIC]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	ES [Single]	CCR-F | M3	CCR-F | M3	ES [Single]	ES [Single]	ES [Single]	ES [Single]
RMSPE	1.945	5.713	9.442	14.319	18.092	24.271	2.015	5.590	9.443	14.319	18.095	24.270
Best DESARIMA	[8]	[8]	[8]	[7]	[7]	[7]	[8]	[1]	[1]	[10]	[9]	[9]
RMSPE	1.449***	4.237**	7.919**	14.271	17.923	24.162	1.860	5.129	9.067	14.274	17.867	24.149
United Kingdom												
Best benchmark	ES [Single]	ES [Single]	AR [AIC]	AR [AIC]	AR [AIC]	ES [Single]	ES [Single]	ES [Single]	CCR-F | M4	CCR-F | M4	ES [Single]	ES [Single]
RMSPE	0.303	0.576	0.822	0.942	0.978	0.995	0.303	0.579	0.831	0.972	1.097	0.995
Best DESARIMA	[2]	[2]	[2]	[1]	[1]	[6]	[8]	[8]	[8]	[6]	[6]	[6]
RMSPE	0.259***	0.485**	0.711	0.944	1.030	0.995	0.262**	0.496*	0.765	1.088	1.097	0.995
United States												
Best benchmark	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)	AR [BIC]	AR [BIC]	AR(1)	ARMA [AIC]	ARMA [AIC]	ARMA(1,1)	AR [AIC]	ARMA [BIC]	ARMA(1,1)
RMSPE	0.483	1.083	1.503	1.686	1.696	1.604	0.442	1.003	1.350	1.490	1.438	1.492
Best DESARIMA	[4]	[4]	[4]	[5]	[4]	[1]	[4]	[4]	[4]	[5]	[4]	[3]
RMSPE	0.371***	0.841***	1.208**	1.637	1.562**	1.522**	0.331***	0.751**	1.099**	1.495	1.471	1.487

See tables 1 and 2 for DESARIMA and benchmark and specifications. GW test: * p<10%, ** p<5%, *** p<1%. Source: Authors' computations.

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