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TEMPORAL DISAGGREGATION TECHNIQUES OF TIME SERIES BY RELATED SERIES: A COMPARISON BY A MONTE CARLO EXPERIMENT [1]

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This work presents a comparison of different techniques for disaggregating annual flow time series by a quarterly related indicator, based on a Monte Carlo experiment. A first goal of the study is related to the estimation of the autoregressive parameter implied by the solution proposed by Chow and Lin (1971), which is the most used technique by National Statistical Institutes (NSI). Three estimation approaches have been considered, being the more recurrent in the literature: the inversion of the relationship linking the first order aggregated autocorrelation and the autoregressive parameter at the highest frequency (Chow and Lin, 1971), the maximization of the log-likelihood (Bournay and Laroque, 1979), and the minimization of the sum of squared residual (Barbone, Bodo, and Visco, 1981). We evaluate the accuracy of the estimated autoregressive parameter from these approaches and compare the disaggregated series obtained with the simulated ones. Then, the comparison is extended to other regression-based techniques based on the proposals by Fernández (1981), Litterman (1983), Santos Silva and Cardoso (2001) and Di Fonzo (2002). Nearly one hundred and fifty scenarios were designed, in order to detect the conditions that allow each technique to obtain the best disaggregation (in terms of in-sample and out-of-sample accuracy), verify whether a technique outperforms the other ones and evaluate the efficiency of the parameter estimates obtained maximizing the log-likelihood and minimizing the sum of squared residuals.

Keywords: Temporal disaggregation by related series, Monte Carlo simulation, Quarterly national accounts.

JEL classification: C22, C13, C15.

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1 Introduction

The frequency at which official statistics are released by National Statistical Institutes (NSI) or other data producers is decided on the basis of several factors: the nature of the underlying phenomenon, the burden of respondents, budgetary constraints, etc. It follows that official time series are often available at lower frequency than users would like. The lack of high frequency indicators could be overcome with the help of mathematical, statistical or econometric techniques to interpolate, distribute or extrapolate the missing values at the desired frequency. Such methods go under the name of temporal disaggregation (or benchmarking) techniques. Often, NSI themselves rely on such methods when a direct estimation approach cannot be accomplished: the indirect approach followed by some European NSI in the estimation of quarterly national accounts (QNA) is a clear example. This task is usually performed using techniques which base the disaggregation on one (or more) indicator series, available at an higher frequency, somehow related to the objective series. Chow and Lin (1971) derive a general formulation of the disaggregation problem. They obtain a least-square optimal solution in the context of a linear regression model involving the missing series and the related indicators; moreover, they suggest to impose a first-order autoregressive structure to the residual term. This solution requires an estimation of the autoregressive parameter at the high-frequency (HF) level, which, however, can only be inferred by the relationship of the variables at the lower frequency (LF). Since the temporal aggregation alters much of the properties of the HF autoregressive process, an exact identification from the LF residuals is not possible.

Different strategies have been developed to get an estimate of the autoregressive parameter from the LF data: the most applied procedures are those proposed by Chow and Lin (1971), Bournay and Laroque (1979) , and Barbone, Bodo, and Visco (1981) and will be illustrated in the next section. In the meantime, other authors have proposed alternative restrictions on the DGP of the disturbance series in the HF regression model. Fernández (1981) proposes a random walk model for the disturbances that avoids the estimation of parameters at the HF level. Litterman (1983) refines the Fernández solution by introducing a Markov process to take account of serial correlation in the residuals. Wei and Stram (1990) encompasses the three solutions, generalizing the restriction in the class of ARIMA (AutoRegressive Integrated Moving Average) processes. Recently, some authors have proposed techniques based on dynamic regression models in the identification of the relationship linking the series to be estimated and the related indicators. We refer to the works of Salazar, Smith, and Weale (1997), Salazar, Smith, Weale, and Wright (1997), Santos Silva and Cardoso (2001), and Di Fonzo (2002).

An empirical comparison of the performances of temporal disaggregation techniques might be obtained by using real-world data. Many series of interest are however observed only at annual/quarterly level, so that any judgement on the performance of a method can merely be done by measuring distances between the disaggregated series and the related quarterly/monthly indicators. This paper instead presents evidence based on a simulation study which investigates on the relative quality of the estimates from alternative solutions and estimation methods. The objective series are derived as sum of two components, the indicator series and the disturbance series both simulated at the HF level. Hence, the series of interests are completely known at the desired frequency and can be used as benchmarks for evaluating the disaggregated series.

Comparative studies of disaggregation techniques with simulated time series have already been developed but, in our opinion, they are based on too restrictive hypotheses concerning the data generation process used to simulate the series and the type and the number of alternative methods compared. Chan (1993) compares the quarterly disaggregation procedure by Wei and Stram (1990) with other five methods which do not make use of related indicators. A similar exercise has been recently presented by Feijoo, Caro, and Quintana (2003), which consider a more refined simulation design to take account of seasonal components in the simulated series. Pavia, Vila, and Escuder (2003) perform a simulation experiment in order to assess the quality of the estimates obtained through the disaggregation procedure proposed by Chow and Lin (1971), but only an estimation strategy (similar to those suggested by Chow and Lin) has been used. Finally, Caro, Feijo, and Quintana (2003) extend the comparison to other proposals based on the best linear unbiased solution given by Chow-Lin. The evaluation of the methods is fairly different with respect to our work because they do not consider any admissibility condition of the solutions; furthermore, the method based on the dynamic regression model is not taken into consideration in their analysis.

The last two references are strictly connected with our work. The scenarios considered are similar to those composed in our experiment (in section 3 we will explain the main differences). In a first exercise we compare the performances of the three estimation methods for the Chow-Lin solution mentioned earlier. The methods are assessed in terms of estimation accuracy of the autoregressive parameter (and of the disaggregated series) under a Markov-process hypothesis for the disturbance series and different DGPs for the indicator series. Then, the comparison is extended to other regression-based proposals based on the Chow-Lin approach. In this second exercise we also introduce an integration of order one in the disturbance series, as implied by the Fernández and Litterman proposals. This allows to verify if each method works properly when the simulated and the assumed HF disturbance series are coherent. The dynamic solution proposed by Santos Silva and Cardoso (2001) and re-arranged by Di Fonzo (2002) is also included in our analysis, even if we must say that the comparison with the other solutions is unfair because the reference model used in the simulation is essentially static.

The structure of the paper is as follows. In the next section we introduce the statement of the disaggregation problem, providing a review of the methods we intend to compare. Section 3 describes the simulation design used in our experiment. In Section 4 we present and discuss the most interesting results obtained from the two exercises. Conclusions are drawn in the final section.

2 A brief review on temporal disaggregation methods

The objective of any temporal disaggregation technique is to derive an estimate of the underlying high-frequency (HF) observations of an observed low-frequency (LF) time series. This problem is also known as interpolation (for stocks) or distribution (for flows) of time series (in this paper we only consider distribution of flow time series so we will refer to it hereafter). Let us denote a vector of LF data by

$$\mathbf{y}_l = (y_1, y_2, \ldots, y_T)'$$

and the corresponding vector of (missing) HF observations by

$$\mathbf{y}_h = (y_{1,1}, y_{1,2}, \ldots, y_{T,s-1}, y_{T,s})'$$

with s the periodicity of $\mathbf{y}_h$. The naive solution of the problem is to divide each value of $\mathbf{y}_l$ by s. Such a solution is reasonable if we suppose a straight line connecting the HF periods between subsequent LF observations. This is certainly not the case for economic time series, because seasonal, cyclical and irregular components do influence their movements at sub-annual frequencies. How then is it possible to get more acceptable results both in the statistical and economic sense? The problem have been approached in different manners by the literature. Di Fonzo (1987) provides a useful classification of the methods into the following two categories:

- methods which derive disaggregation of the LF values using mathematical criteria or time series models;
- methods which exploit external variables observed at the desired frequency.

The main references for the first approach are Boot, Feibes, and Lisman (1967), Lisman and Sandee (1964) and Wei and Stram (1990). The latter proposal is more theoretically founded because the distribution problem is solved on the basis of an ARIMA representation of the series to be disaggregated. The methods belonging to the second group exploit the information from related time series. A further classification in this group is between two-step adjustment methods and optimal methods. The former techniques obtain a preliminary disaggregated series which does not fulfil the temporal constraint; a second step is then required to adjust the HF series to the LF totals. The proposal by Denton (1971) is the most known two-step adjustment procedure. The solutions in the second group are optimal in the least-squares sense because they solve the preliminary estimation and adjustment steps in the context of a statistical regression model which involves LF variables and HF related series.

Since optimal methods are the primary interest of this paper, we illustrate in detail the proposals (along with estimation methods) we intend to compare. Let us first introduce some basic notation. Suppose a $n \times k$ matrix of related time series $\mathbf{X}_h$ is available, with

$n \geq sT$. If $n = sT$ we face a distribution (or interpolation) problem; for $n > sT$, the last $(n - sT)$ HF sub-periods need to be extrapolated. Any deterministic term (constant, trend or similar) might or might not be included in $\mathbf{X}_h$. The following regression model is assumed at the HF level

$$\mathbf{y}_h = \mathbf{X}_h \beta + \mathbf{u}_h \tag{1}$$

where β is the vector of regression coefficients and $\mathbf{u}_h$ is the disturbance series. As we will see later, the optimal solution differs for the hypothesis on the underlying DGP of $\mathbf{u}_h$. For the time being, suppose

$$\begin{aligned} E(\mathbf{u}_h|\mathbf{X}_h) &= \mathbf{0} \\ E(\mathbf{u}_h\mathbf{u}_h'|\mathbf{X}_h) &= \mathbf{V}_h \end{aligned}$$

without specifying any form for $\mathbf{V}_h$.

Pre-multiplying both members of model (1) by the $T \times n$ aggregation matrix $\mathbf{C}$, defined as

$$\mathbf{C} = \mathbf{I}_T \otimes \mathbf{1}'$$

where $\mathbf{1}$ is the $s \times 1$ vector of ones, we obtain the LF counterpart of (1)

$$\begin{aligned} \mathbf{C}\mathbf{y}_h &= \mathbf{C}\mathbf{X}_h\beta + \mathbf{C}\mathbf{u}_h \\ \mathbf{y}_l &= \mathbf{X}_l\beta + \mathbf{u}_l. \end{aligned} \tag{2}$$

with $E(\mathbf{u}_l\mathbf{u}_l'|\mathbf{X}_h) = \mathbf{C}\mathbf{V}_h\mathbf{C}' = \mathbf{V}_l$.

Being observable, model (2) can now be estimated by standard techniques. The optimal solution (in the BLUE sense) is formally obtained through the expressions

$$\widehat{\mathbf{y}}_h = \mathbf{X}_h\widehat{\beta} + \mathbf{V}_h\mathbf{C}'\mathbf{V}_l^{-1}(\mathbf{y}_l - \mathbf{X}_l\widehat{\beta}) \tag{3}$$

$$\widehat{\beta} = [\mathbf{X}_l'\mathbf{V}_l^{-1}\mathbf{X}_l]^{-1}\mathbf{X}_l'\mathbf{V}_l^{-1}\mathbf{y}_0 \tag{4}$$

where $\widehat{\beta}$ is the least square estimator of β in the LF regression (2).

The estimator of β and, consequently, the estimated series $\widehat{\mathbf{y}}_h$ is conditioned to the form of $\mathbf{V}_h$. If $\mathbf{V}_h = \mathbf{I}_n\sigma_\varepsilon^2$, expression (4) corresponds to the OLS formula and (3) becomes

$$\widehat{\mathbf{y}}_h = \mathbf{X}_h\widehat{\beta} + \mathbf{C}'(\mathbf{C}\mathbf{C}')^{-1}(\mathbf{y}_l - \mathbf{X}_l\widehat{\beta});$$

since $\mathbf{C}\mathbf{C}' = s\mathbf{I}_T$, then

$$\widehat{\mathbf{y}}_h = \mathbf{X}_h\widehat{\beta} + \frac{1}{s}\mathbf{C}'(\mathbf{y}_l - \mathbf{X}_l\widehat{\beta}),$$

obtaining the naive solution we have started from. A non-spherical form of the noise is thus essential: the problem is that this form is unknown. Two alternative strategies can be used to define the form of $\mathbf{V}_h$. First, an estimate of $\mathbf{V}_h$ can be inferred by the empirical measure of the aggregate covariance matrix $\mathbf{V}_l$. The form of $\mathbf{V}_h$ is thus suggested by the data at hand. This is the approach followed by Wei and Stram (1990). However, two orders of problems arise from this approach. Firstly, the covariance matrix of the HF disturbances cannot be uniquely identified from the relationship $\mathbf{V}_l = \mathbf{C}\mathbf{V}_h\mathbf{C}'$. Next, the approach relies heavily on ARIMA model identification for the aggregate series. Economic time series have generally a small sample size, so that the estimated autocorrelations at the LF level (say, annual) have poor sample properties. As an alternative approach, some authors proposed to restrict the DGP of $\mathbf{u}_h$ to well-known structure in the class of ARIMA processes. The pioneers of this approach are surely Chow and Lin (1971). Their work has had an enviable success in the field of temporal disaggregation: some European NSI currently base the compilation of their QNA on this method (for example Italy, France, and Belgium). The Chow-Lin solution is in fact understandable, easy to apply, fast and robust: features that are very appealing from the standpoint of a data producer.

Chow and Lin (1971) present a common solution to the problems of distribution, interpolation and extrapolation using the theory of best linear unbiased estimation. Moreover, they suggest the simple Markov process for $\mathbf{u}_h$

$$u_t = \rho u_{t-1} + \varepsilon_t \tag{5}$$

for $t = 1, ..., n$ and $u_0 = 0$. It follows that the covariance matrix $\mathbf{V}_h$ has a Toeplitz form

$$\mathbf{V}_h = \frac{\sigma_\varepsilon^2}{1-\rho^2}\begin{bmatrix} 1 & & & & \\ \rho & 1 & & & \\ \rho^2 & \rho & 1 & & \\ \cdots & \cdots & \cdots & 1 & \\ \rho^{n-1} & \rho^{n-2} & \rho^{n-3} & \cdots & 1 \end{bmatrix}$$

with $E(\varepsilon_t^2) = \sigma_\varepsilon^2$. The matrix $\mathbf{V}_h$ would be completely defined if the autoregressive parameter ρ were known. In this case $\widehat{\beta}$ is the GLS estimator of β. The real problem is that ρ is not known and must be estimated: it follows that $\widehat{\beta}$, conditional to $\widehat{\rho}$, is a feasible GLS estimator of β. If $\widehat{\rho} = 0$, the matrix $\mathbf{V}_h$ is diagonal and the distribution of the annual discrepancies $(\mathbf{y}_0 - \mathbf{C}\mathbf{X}\widehat{\beta})$ is simply obtained dividing by four each value, inducing the spurious jumps in the series we would like to avoid. Different estimated values of ρ imply different estimates of $\widehat{\beta}$ and, consequently, different estimated disaggregations.

Different estimation methods have been proposed to obtain an estimate of ρ from LF variables. We concentrate here on three approaches, the more recurrent in the literature. A first method has been proposed in the paper of Chow and Lin (1971). Their method considers the relationship between ρ and the elements of the aggregated covariance matrix $\widehat{\mathbf{V}_l}$. They propose a strategy based on the relationship between the autoregressive coefficient at monthly level with the first autocorrelation computed from the quarterly errors, which is the element [1,2] of $\widehat{\mathbf{V}_l}$. The strategy originally proposed by Chow-Lin cannot be immediately extended to the problem of quarterly disaggregation of annual figures, as indicated by Bournay and Laroque (1979). The quarterly autoregressive coefficient ρ and the first-order autocorrelation of the annual disturbances ϕ_1^a are related through the following expression:

$$\phi_1^a = \frac{\rho(\rho+1)(\rho^2+1)^2}{2(\rho^2+\rho+2)}. \tag{6}$$

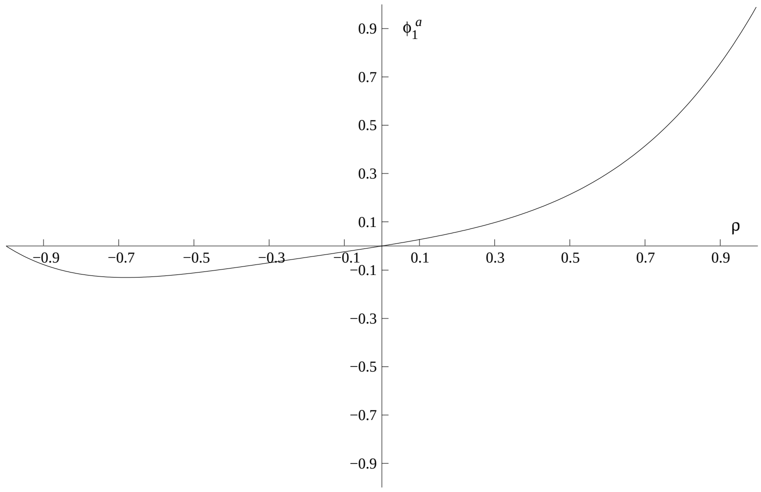

Figure 1: Plot of ϕ_1^a against ρ.

An iterative procedure is then applied to derive an estimate of ρ. From an initial estimate of ϕ_1^a from the OLS residuals of (2), the value of $\widehat{\rho}$ is continuously obtained replacing the new values of ϕ_1^a in expression (6). The iterations end up when $\widehat{\rho}$ converges around a stable value with a fixed precision level.

The aggregation of a quarterly first-order autoregressive process yields an ARMA(1,1) process at annual frequency. This means that ϕ_1^a depends on both AR and MA coefficients, so that there is not a biunivocal correspondence between the two coefficients because of the MA part (the quarterly autoregressive parameter is simply given by ρ^4). This is the reason why the iterative procedure of Chow-Lin does not obtain a solution for some values of ϕ_1^a. This occurs for $\phi_1^a < -0.13$; moreover, when $-0.13 < \phi_1^a \leq 0$ equation (6) has two solutions. This can be easily verified in the plot of ρ against ϕ_1^a shown in Figure (2). In these cases a quarterly disaggregation cannot be achieved.

Bournay and Laroque (1979) present an alternative estimation procedure based on the maximization of the log-likelihood. Assuming normality of the residuals, the log-likelihood of a regression model with AR(1) disturbances can be defined as

$$\log L(\widehat{\rho}; \widehat{\beta}) = \frac{n}{2}(-1 - \ln(\frac{2\pi}{n})) - \frac{n}{2}\ln(\widehat{\mathbf{u}}_l \mathbf{V}_l^{-1} \widehat{\mathbf{u}}_l') - \frac{1}{2}\ln(|\mathbf{V}_l|).$$

The log-likelihood can be maximized with respect to ρ in the region of stationarity $(-1; 1)$. The optimization is obtained through an iterative computation of the matrix $\mathbf{V}_h$, the vectors β and $\mathbf{u}_l$ for a grid of values of ρ. The ML estimate of ρ is that for which $\log L(\widehat{\rho}; \widehat{\beta})$ is maximum over this grid.

The third approach is that outlined in Barbone, Bodo, and Visco (1981). The authors propose to choose the value of ρ minimizing the sum of squared residuals, $\widehat{\mathbf{u}}_l \mathbf{V}_l^{-1} \widehat{\mathbf{u}}_l'$. They refer to it as an Estimated Generalized Least Squares (EGLS) estimator. Di Fonzo (1987) shows that this solution appears to give better results than ML when sharp movements are present in the series.

As we mentioned earlier, the quarterly disaggregation of annual national accounts aggregates are obtained by some European NSI through the application of the Chow-Lin technique. The variant by Barbone, Bodo, and Visco (1981) is currently applied by ISTAT, the Italian NSI, in the compilation of quarterly national accounts. An algorithm similar to those of Chow and Lin (1971) is used by INE, the Spanish NSI, while the Bournay and Laroque's solution is adopted by the Belgium statistical agency. A comparative assessment of the three estimation approaches is the objective of our first Monte Carlo experiment.

So far, we have presented an outline of the literature connected to the Chow and Lin's suggestion of using an AR(1) structure for $\mathbf{u}_h$. Some criticisms to this solution come from Fernández (1981). The specification of a variance-covariance matrix is impossible because the data are not observed at the HF level. Furthermore, the AR(1) hypothesis might introduce an artificial step between the last period of one year and the first period of the next. The alternative structure for the HF noise proposed by Fernández is the random walk model

$$u_t = u_{t-1} + \varepsilon_t \tag{7}$$

with $u_0 = 0$.

The advantage of this solution is that the form of $\mathbf{V}_h$ is completely known without requiring any estimation procedure. In fact, the initial condition is sufficient to guarantee its existence. Assuming

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix},$$

the matrix $\mathbf{V}_h$ is defined as

$$\mathbf{V}_h = \sigma_\varepsilon^2(\mathbf{D}'\mathbf{D})^{-1} = \begin{bmatrix} 1 & 1 & \cdots & 1 & 1 \\ 1 & 2 & \cdots & 2 & 2 \\ 1 & 2 & \cdots & 3 & 3 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 2 & \cdots & n-1 & n \end{bmatrix}.$$

Model (1) with hypothesis (7) imply that β is not a cointegrating vector for $\mathbf{y}_h$ and $\mathbf{X}_h$: the objective variable and the related series are thus to be modelled in difference form.

An interesting extension of the Fernández proposal is obtained by the use of the logarithmic transformation of $\mathbf{y}_t$ (Di Fonzo, 2002). The absence of additivity of log-transformed variables can be worked around by using Taylor approximations and benchmarking techniques to fulfil temporal constraints if discrepancies are relatively large. Setting $\mathbf{z}_h = \log(\mathbf{y}_h)$ and expressing the HF model in first differences, we obtain

$$\Delta \mathbf{z}_h = \Delta \mathbf{X}_h \beta + \varepsilon_h, \tag{8}$$

a model expressed in terms of rates of change of $\mathbf{y}_h$ (approximated by its logarithmic difference). This solution seems appealing because many economic models are expressed in terms of growth rates of the variable of interest. Moreover, from the aggregation of model (8) we obtain a model expressed in terms of the low-frequency rate of change (approximately). In other terms, the estimated model at the LF level are fully coherent with the theoretical model supposed at the HF level.

A further modification of the procedure of Fernández (1981) is offered by Litterman (1983). In several applications he found that the random walk assumption for the monthly error term did not remove all of the serial correlation. As an alternative, he suggests the random walk Markov model

$$\begin{aligned} u_t &= u_{t-1} + e_t \\ e_t &= \psi e_{t-1} + \varepsilon_t \end{aligned} \tag{9}$$

with $|\psi| < 1$ and the initial conditions $u_0 = e_0 = 0$, for $t = 1, ..., n$. He compares this method with both the Chow-Lin and Fernández solutions on some real world economic time series; his results indicate that hypothesis (9) is more accurate than others when the estimated Markov parameter $\hat{\psi}$ is positive.

Both Fernández and Litterman impose fixed conditions on the history of the disturbance process. During the work of the ISTAT commission (see footnote 1), Proietti (2004) and Di Fonzo (2005b) investigate on the role of the starting conditions to deal with nonstationary disturbances and provide a new parametrization of the problem which does not need the assumption that the starting value be fixed.

The methods illustrated above are all based on a static regression model between the variable of interest and the related indicators. This can be considered a serious drawback when the relationships are dynamic, as those usually encountered in applied econometrics work. In the recent years there have been several proposals to extend the use of dynamic regression models to temporal disaggregation. Di Fonzo (2002) provides a complete technical review of this line of research. Gregoir (1995) and Salazar, Smith, and Weale (1997) propose a simple dynamic regression model, but the algorithm needed to calculate estimates and standard errors are rather complicated. The same linear dynamic model has been developed by Santos Silva and Cardoso (2001) with a simpler estimation procedure. From the dynamic model

$$y_t = \phi y_{t-1} + \mathbf{x}_t' \beta + \varepsilon_t \tag{10}$$

Santos Silva and Cardoso (2001) apply the recursive substitution suggested by Klein (1958) obtaining the transformed model

$$\begin{aligned} y_t &= \sum_{i=0}^{t-1} (\phi^i \mathbf{x}'_{t-i})\beta + \phi^t \eta + u_t \\ u_t &= \phi u_{t-1} + \varepsilon_t. \end{aligned} \tag{11}$$

The *truncation remainder* η is considered as a fixed parameter and can be estimated from the data. Since model (11) is a static regression model with AR(1) disturbances, the classical Chow and Lin's procedure can be applied to obtain an estimate of ϕ and, consequently, of the disaggregated series in accordance with the dynamic regression model (10).

3 The simulation design

A simulation exercise in the context of temporal disaggregation requires (at least) the generation of two variables, the low-frequency benchmark and one (or more) high-frequency indicator. To simplify notation, we only consider quarterly disaggregation of annual series by means of a single related indicator. We denote the annual variable as y_t and the quarterly indicator as $x_{t,h}$, with $t = 1, \ldots, T$ and $h = 1, \ldots, 4$. The two series must be related somehow. We use the following static relationship between the indicator series $x_{t,h}$ and the quarterly variable $y_{t,h}$

$$y_{t,h} = \alpha + \beta x_{t,h} + u_{t,h} \tag{12}$$

where α and β are parameters to generate and $u_{t,h}$ represents a quarterly series generated independently from $x_{t,h}$. The series $u_{t,h}$ is denoted as the disturbance series. Since we are dealing with the distribution problem, the annual benchmark y_t is easily obtained by summing up the quarters $y_{t,1}, ..., y_{t,4}$ for any $t = 1, ..., T$.

The relationship (12) ensures the strong exogeneity of the indicator series with respect to y_t. The signal $x_{t,h}$ is "perturbated" by the noise $u_{t,h}$, which can be derived from a process of any nature (stationary, integrated, seasonal, etc.). Clearly, the more complex is the structure of $u_{t,h}$ the lower is the signal preserved in y_t. It follows that the exogenity of $x_{t,h}$ is a strong condition of our simulation model, not allowing a joint interaction between variables and related indicators over time. Though this solution may appear not very appealing from a theoretical point of view, the extent of our experiment needs a simpler approach.

As a matter of fact, a simulation exercise based on the model (12) consists of various steps:

1. generation of both the indicator series $x_{t,h}$ and the disturbance term $u_{t,h}$ fulfilling the orthogonality condition;

2. generation of the parameters α and β;

3. derivation of the dependent series $y_{t,h}$ in accordance with different level of adequacy of the model fit;

4. computation of the annual benchmark y_t;

5. temporal (monthly or quarterly) disaggregation of y_t based on the related indicator $x_{t,h}$ by different disaggregation techniques and estimation methods;

6. comparison of the estimated HF data $\hat{y}_{t,h}$ (and the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$) with the generated data $y_{t,h}$ (and the true parameters α and β) in order to assess the accuracy of the estimates.

Here we deal with the first four steps, whereas the last ones are described in the next section as they concern the results and their assessment.

As far as the first step is concerned, the indicator series and the disturbance term are both generated according to ARIMA models. An ARIMA model can be expressed, apart from a constant, as

$$\phi(L)\Phi(L^s)(1-L)^d(1-L^s)^D x_{t,h} = \theta(L)\Theta(L^s)a_{t,h}, \tag{13}$$

where: (i) $\phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$, $\Phi(L^s) = 1 - \Phi_1 L^2 - \ldots - \Phi_P L^{sP}$, $\theta(L) = 1 - \theta_1 L - \ldots - \theta_q L^q$ and $\Theta(L^s) = 1 - \Theta_1 L^s - \ldots - \Theta_Q L^{sQ}$ are finite polynomials in the lag operator L, of order p, P, q and Q; (ii) $s = 4(12)$ for quarterly (monthly) observations; (iii) $a_{t,h}$ is a sequence of $NIID(0, \sigma^2)$ variables.

A multitude of ARIMA specifications can be defined from (13). To choose among them, hundreds of series currently used in the process of estimating QNA were analysed using the procedure TRAMO-SEATS (Gomez and Maravall, 1997). The ARIMA models, automatically identified, were ranked according to the number of series they were fitted on.[3] In our experiment, this empirical results allow us to consider very simple models with $d, D, p, q, Q = 0, 1$, $P = 0$, $s = 4$ and $\sigma^2 = 1$; a constant term is added in order to obtain positive data. These data are then multiplied by a scale factor to guarantee a minimum amount of volatility in the indicators. Table 1 displays the models chosen to generate the indicators and their coefficients (ϕ, θ and Θ). These are fixed to the average of the parameter estimates coming from the real series.

[3]The series currently used to estimate QNA and analysed in this paper are indicators of the industrial production, the compensations of employees and the household consumptions. These last indicators, in number index form, are just used to produce QNA data and are not released to the final users.

Table 1: ARIMA models and parameters used to generate the indicator series.

ARIMA models	Parameters ϕ	θ	Θ	Seasonal adjustment	Name
$(0,1,1)(0,1,1)$	-	0.4	0.6	no / yes	I1 / I1sa
$(0,1,0)(0,1,1)$	-	-	0.6	no / yes	I2 / I2sa
$(1,0,0)(0,1,1)$	0.4	-	-	no / yes	I3 / I3sa
$(0,1,1)$	-	0.4	-	no	I4

A seasonal adjusted version of the indicator series is obtained by applying TRAMO-SEATS.[4] In order to best reproduce the ordinary compilation of QNA, the seasonal adjustment is carried out identifying the ARIMA models and estimating their parameters automatically. Clearly, the estimated models may differ from the ARIMA processes used to generate the raw series.

The innovation series $a_{t,h}$ is derived from a standardized normal distribution using the GAUSS function *rndn* based on the algorithm proposed by Kinderman and Ramage (1976). A Ljung-Box test is performed to verify the randomness of $a_{t,h}$: when the Ljung-Box statistic computed on the first 16 autocorrelations exceeds the value corresponding to a 10% probability level, the generated series is discarded and replaced with a new one. In order to reduce the effect of the initial condition $a_0 = 0$, $4T + 100$ observations are first generated for the disturbance term and the first 100 observations are then discarded from the final indicator series.

As far as the model for the disturbance series is concerned, we have to distinguish two different contexts. The first context is the comparison of three estimation methods used in the Chow-Lin's solution, then the disturbance series are generated from simple first-order autoregressive model:

$$u_{t,h} = \rho u_{t-1,h} + \varepsilon_{t,h}. \tag{14}$$

Since different values of ρ may produce strong changes in the properties of the estimation methods, we simulate nineteen configurations of (14) with $\rho = 0.05, 0.10, \ldots, 0.90, 0.95$. Hereinafter, we denote this simulation exercise by $E1$.

When the purpose of the simulation exercise is the comparison among various disaggregation techniques, the disturbance series are not only generated from (14), but also from a simple random walk model (supposed in the Fernández's approach)

$$u_{t,h} = u_{t-1,h} + \varepsilon_{t,h}. \tag{15}$$

[4]The generation of seasonal series and the next seasonal adjustment could seem a pointless complication as in economic short-term analysis infra-annual data are mainly used in seasonal adjusted form. Actually, such a process meets the requirements of the European regulation. In accordance to European System of Accounts (ESA95), NSI are required to produce both raw and seasonally adjusted QNA.

and from a Markov-random walk model (supposed in the Litterman's approach)

$$\begin{aligned} u_{t,h} &= u_{t-1,h} + e_{t,h} \\ e_{t,h} &= \phi e_{t-1,h} + \varepsilon_{t,h}. \end{aligned} \tag{16}$$

Because of the computational complexity of the experiment, in this second exercise, denoted by $E2$, we simulate three configurations of (14), (15) and (16) with $\rho, \phi = 0.1, 0.5, 0.9$ (see table 2).

Table 2: ARIMA models and parameters used to generate the error series in exercise $E2$.

ARIMA models	ρ	Name	ARIMA models	ϕ	Name
	0.1	C1		0.1	L1
$(1,0,0)$	0.5	C5	$(1,1,0)$	0.5	L5
	0.9	C9		0.9	L9
$(0,1,0)$	-	F			

The innovation series $\varepsilon_{t,h}$ is drawn with the same properties of $a_{t,h}$.

Two transformations are applied to the generated disturbance series: (i) a constant term is added to obtain positive data; (ii) the standard deviation, σ_u, is changed in order to perturb the signal of the indicator series. The former transformation modifies the average of the series; the latter one implies a modification of the coefficient of determination R^2, according to the formula:

$$\sigma_u^* = \sqrt{\frac{1 - R^2}{R^2}\,\beta^2 \sigma_x^2}. \tag{17}$$

The final error series are then derived as

$$u^* = \frac{\sigma_u^*}{\sigma_u}\,u. \tag{18}$$

Clearly, for larger values of R^2, we expect better results from all the estimation methods and the disaggregation techniques. To avoid useless and overlapping results, in the experiment $E1$ the coefficient of determination is fixed to $R^2 = 0.9$, whereas in $E2$ three different levels are considered with $R^2 = 0.3, 0.6, 0.9$.

Finally, to complete expression (12) we have to choose the values for the constant α and the regression coefficient β. In order to understand their effects on the simulation results, we tried two ways. First, we extracted different couples of values for (α, β) from uniform distributions; then, we kept fixed the coefficients to $\alpha = 100.000$ and $\beta = 1$ throughout the experiments. Given the similarity of the results achieved, we chose the latter approach. Moreover, on the one hand, the large constant makes the simulated series $y_{t,h}$ similar to a generic QNA aggregate in value and helps the interpretation of results in terms of growth rates; on the other hand, fixed regression coefficients allow us to assess bias and standard error of the respective estimates.

The quarterly simulated series $y_{t,h}$ is then aggregated over time using the matrix expression

$$\begin{aligned}
\mathbf{y}_0 &= (\mathbf{I}_T \otimes \mathbf{1}'_4)\mathbf{y} \\
\mathbf{y}_0 &= \begin{pmatrix} y_1 & y_2 & \cdots & y_T \end{pmatrix}' \\
\mathbf{y} &= \begin{pmatrix} y_{1,1} & y_{1,2} & y_{1,3} & y_{1,4} & \cdots & y_{T,3} & y_{T,4} \end{pmatrix}'
\end{aligned}$$

where $\mathbf{I}_T$ is the identity matrix of dimension T and $\mathbf{1}_4 = \begin{pmatrix} 1 & 1 & 1 & 1 \end{pmatrix}'$.

The number of years used in the experiments is $T = 26$ (104 quarters): twenty-five years are used for the estimation of the regression model, while the last year is left apart to evaluate the forecasting performance of the methods. Combining the indicator and the disturbance series, 261 scenarios are generated in all: 114 of them concern the exercise $E1$, the other ones (147) the exercise $E2$. For each scenario, 500 couples (with a quarterly indicator and an annual benchmark) are first generated and then processed using two or three estimation methods and various disaggregation approaches, running almost two million disaggregations!

The grid search for the autoregressive parameter is performed in the interval $[-0.999, 0.999]$. To reduce the computational time, we adopt a two-stage scanning procedure. In each stage a 25-step grid search is used to optimize the objective function; when in the first stage a solution $|\hat{\rho}| > 0.92$ is achieved, a finer grid of 51 steps is used. This choice will be clearer in section 4; here we only sketch that a finer grid near the bounds ± 1 is required because some solutions (i.e. $|\hat{\rho}| > 0.998$) are considered non-admissible and rejected.

All the experiments are performed in GAUSS 4.0 and the temporal disaggregations are carried out using the GAUSS routine TIMEDIS.g (Di Fonzo, 2005a). Two personal computers with AMD Athlon XP 2400 processor 2.4 Ghz and 240 Mb RAM are employed.

4 The simulation results

The following two sub-sections show the main results of exercises $E1$ and $E2$. The differences of the experimental design have been already described; we now specify which methods have been taken into account and how the results have been evaluated in each experiment.

A common element of both exercises is the distinction between admissible and non-admissible solutions. We consider a solution acceptable when the following two conditions are contemporaneously fulfilled: the estimated value of the autoregressive coefficient lies in the region of stationarity and the disaggregated series does not contain any negative value. The rationale behind this choice is both theoretical and pragmatic. When a stationary autoregressive component is supposed for the disturbance term, we cannot accept solutions on the boundaries of the interval (namely $(\widehat{\rho}, \widehat{\phi}) = -0.999$ or $(\widehat{\rho}, \widehat{\phi}) = 0.999$). In these cases a theoretical assumption is very likely to be violated and the resulting disaggregations must not be considered. On the other hand, the presence of negative values in the quarterly disaggregation when the annual variable assumes only positive values is an unpleasant result, especially when it is in contrast with the definition of the variable (like GDP or consumption).

The question of admissibility of the solutions is particularly relevant in exercise $E1$, the comparative study of the three estimation methods for the Chow-Lin approach illustrated in section 2, hereafter denoted with CL (Chow and Lin, 1971), ML (Bournay and Laroque, 1979) and SSR (Barbone, Bodo, and Visco, 1981). As we noticed in section 2, CL method provides non admissible solutions for certain values of ϕ_1^a. The other estimation methods can instead provide estimated values for ρ on the boundaries. We noted in the experiments that the condition $\widehat{\rho} = 0.999$ is only verified with SSR, while ML presents several solutions with $\widehat{\rho} = -0.999$. Therefore, each method is characterized by a single non-admissible condition. Differently from the second exercise, we restricted the region of admissibility to $(-0.9; 0.999)$. In fact, the disaggregated series obtained by ML show too erratic movements when $\widehat{\rho} < -0.9$ and are excluded from the calculation of the aggregate statistics.

The estimation methods are evaluated in terms of their accuracy in reproducing the simulated coefficients of the regression model and in terms of quality of the resulting disaggregations, in both in-sample period (100 quarters) and out-of-sample period (4 quarters). Accordingly, the results are organized in two separate sections.

The former concerns the estimation of the three coefficients (α, β, ρ). The estimated regression coefficients α and β are compared to the fixed values used in the experiments, 100000 and 1 respectively. A boxplot representation is used to compare the estimates of β. Given the huge amount of results, measures of aggregation across the time and the experiment dimensions are needed and will be explained later in this section.

The second exercise ($E2$) is a comparison of the performances of several techniques based on the solutions proposed by Chow and Lin (1971), Fernández (1981), Litterman (1983), Santos Silva and Cardoso (2001) and Di Fonzo (2002). Table 3 identifies with acronyms the selected methods, which differ for the regression model, the disturbance model, the estimation method, the deterministic term, the starting condition and the logarithmic transformation used. However, some configurations will not be considered in the next tables because the results obtained were not very interesting. For example, with the logarithmic transformation of the objective series we never obtained significant improvements of the results. To simplify the readability of the tables we will only show the results from the methods shown in boldface, which can be considered as the most performing in our exercises.

Table 3: Disaggregation methods considered in exercise $E2$.

acronyms	*regression model*	*disturbance model*	*estimation method*	*deterministic term*	*starting condition*	*logarithm*
CL ssr	**static**	**ARIMA(1,0,0)**	**SSR**	**constant**	**fixed**	**no**
CL ssr -c	static	ARIMA(1,0,0)	SSR	none	fixed	no
CL ml	**static**	**ARIMA(1,0,0)**	**ML**	**constant**	**fixed**	**no**
CL ml -c	static	ARIMA(1,0,0)	ML	none	fixed	no
FER	**static**	**ARIMA(0,1,0)**	**-**	**constant**	**fixed**	**no**
FER -c	static	ARIMA(0,1,0)	-	none	fixed	no
FER nsc	static	ARIMA(0,1,0)	-	constant	estimated	no
LFER	static	ARIMA(0,1,0)	-	constant	fixed	yes
LFER -c	static	ARIMA(0,1,0)	-	none	fixed	yes
LIT ssr	**static**	**ARIMA(1,1,0)**	**SSR**	**constant**	**fixed**	**no**
LIT ssr -c	static	ARIMA(1,1,0)	SSR	none	fixed	no
LLIT ssr	static	ARIMA(1,1,0)	SSR	constant	fixed	yes
LLIT ssr -c	static	ARIMA(1,1,0)	SSR	none	fixed	yes
LIT ml	**static**	**ARIMA(1,1,0)**	**ML**	**constant**	**fixed**	**no**
LIT ml -c	static	ARIMA(1,1,0)	ML	none	fixed	no
LLIT ml	static	ARIMA(1,1,0)	ML	constant	fixed	yes
LLIT ml -c	static	ARIMA(1,1,0)	ML	none	fixed	yes
LIT nsc	**static**	**ARIMA(1,1,0)**	**ML**	**constant**	**estimated**	**no**
ADL(1,0) ssr	**ADL(1,0)**	**WN**	**SSR**	**constant**	**fixed**	**no**
ADL(1,0) ssr -c	ADL(1,0)	WN	SSR	none	fixed	no
ADL(1,0) ml	**ADL(1,0)**	**WN**	**ML**	**constant**	**fixed**	**no**
ADL(1,0) ml c	ADL(1,0)	WN	ML	none	fixed	no

Again, we verify the estimation accuracy of the regression coefficients. However, to make the comparison fair we only relate estimated and simulated coefficients when the simulated disturbance model is coherent with the assumed one by each method. To make an example, the estimate of β provided by CL ssr is compared with the simulated one only for the experiments with an ARIMA(1,0,0) process for the disturbance series; similar considerations hold for the other two static solutions, while the estimated coefficients by ADL(1,0) (Autoregressive Distributed Lag) are not comparable with any simulated counterpart.

The quality of the disaggregated series is tested by standard measures of comparison. We evaluate the goodness-of-fit of the quarterly series both in-sample and out-of-sample. Denoting with y_t the simulated series and with $\hat{y}_t$ the estimated disaggregation, we compute for each method the root mean square percentage error on the levels (RMSPEL) and the root mean square error on the first-differences (RMSE1) as

$$\text{RMSPEL} = \sqrt{\sum_{t=1}^{100} \left(\frac{\hat{y}_t - y_t}{y_t} 100 \right)^2 \Big/ 100}$$

$$\text{RMSE1} = \sqrt{\sum_{t=2}^{100} \frac{(\delta \hat{y}_t - \delta y_t)^2}{99}}$$

where

$$\delta y_t = \frac{y_t - y_{t-1}}{y_t} 100 \qquad \delta y_t = \frac{y_t - y_{t-1}}{y_t} 100 \; .$$

In exercise $E1$ we also compute a restricted RMSE for the rates of changes corresponding to the first quarters. These are in fact the most critical quarters, in which there might be spurious jumps introduced by a bad disaggregation of the annual figures.

Besides, we analyse the forecasting performance of the methods over the four quarters dropped out from the estimation period. The four extrapolated quarters are annually aggregated to derive the annual extrapolated figure. The percentage error of the extrapolated level (PEL) is computed, while the quarterly growth rates corresponding to the four extrapolated quarters are evaluated with their mean error (ME1) and root mean square error. The former permits to highlight bias in the forecasts, while the latter coincides with the expression given above.

The aggregation across experiments is made by the computation of simple averages and standard errors of the statistics. In order to have a synthetic view on the quality of the methods, we finally construct ranking of the methods based on the averaged statistics.

4.1 Exercise $E1$: a comparison of alternative estimation methods for the Chow-Lin solution

4.1.1 The admissibility of the solutions

Table 4 presents the percentage of non-admissible solutions for the three methods in the different scenarios. These percentages are indicative of the robustness of the disaggregation methods, intended as their ability to give acceptable results to a wide range of situations.

Firstly, the largest percentage of non-admissible solutions is found for CL while this is very low for SSR. The number of non admissible solutions are related to the value of ρ; while ML and CL show a strong inverse relationship, the percentage of non admissible solutions for SSR remains bounded for any value of ρ.

For $\rho = 0.1$ more than 60% of solutions are discarded for CL; the percentage decreases to 30% for $\rho = 0.5$ while for $\rho = 0.9$ a full admissibility of the solutions is obtained. The percentage for ML, around 30% for $\rho \leq 0.5$, rapidly decreases to zero. SSR shows lower percentages for all values of ρ. Moreover, it is worth noting that the non-admissibility condition set for SSR is less dangerous. In fact, when $\hat{\rho} = 0.999$ the estimated series is coherent with the simulated ones. This cannot be said for disaggregations obtained with $\hat{\rho} < -0.9$; in this case the estimated series is affected by sudden changes between positive and negative values which destroy the dynamic of the original series.

These results show that the minimization of the sum of squared residuals is the optimization procedure providing the highest percentage of admissible results. The statistics in the following tables and figures are computed considering only the admissible solutions.

4.1.2 The estimation of parameters

Figure 2 shows the boxplot relative to the estimation of β performed by SSR, ML and CL. Different values of ρ are displayed in columns, while the rows refer to the different indicator models (I1, I2 and I3, not seasonally adjusted). The percentage of admissible solutions is shown in brackets for each method. It is clear from the graphs that the best estimates of β are achieved with the scenario $\rho = 0.1$; as ρ increases, the width of the box (and the length of the whiskers) becomes wider and wider. No regularities are detected across the different indicator models. Looking at the estimation methods, SSR is that showing the poorest performance while ML and CL give roughly the same results.

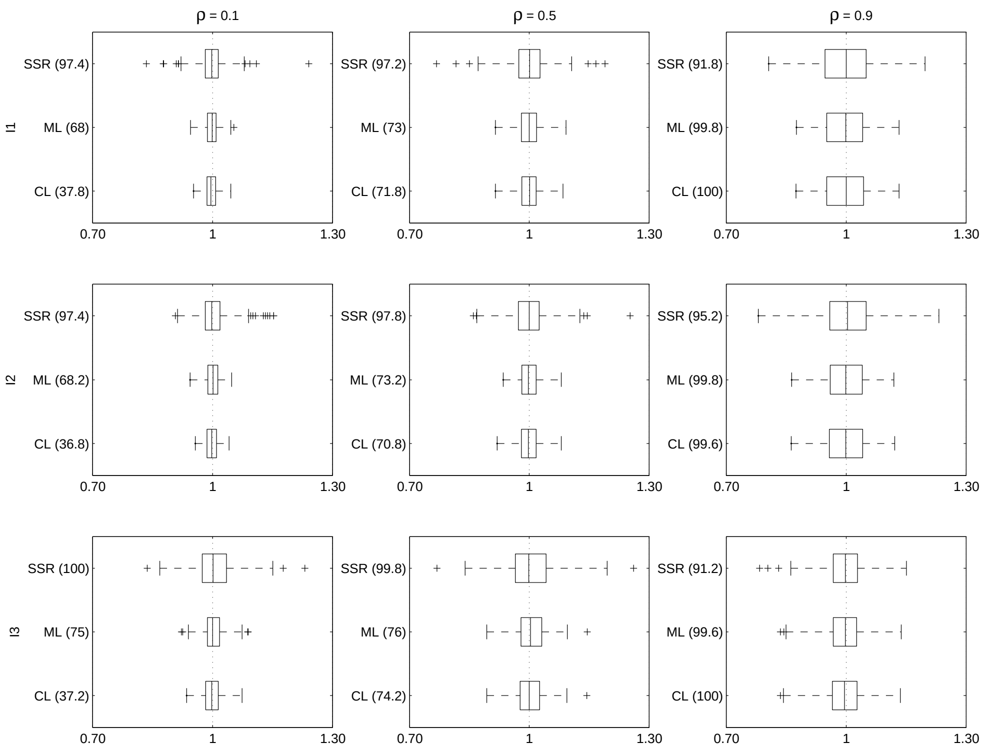

Figure 2: Boxplot relative to the estimation of β.

Table 5 shows the percentage bias and error, averaged across the 500 experiments, relative to the GLS estimators of α and β. Confirming the results in the previous graphs, a lower standard error of the estimates for CL and ML is noticed relative to that of SSR, which always presents a larger volatility.

In Figure 2 the estimated and simulated values of ρ are compared for the three estimation methods (only I1 is considered, being the graphs of the other indicator models very similar). The average and the standard error of the estimates $\hat{\rho}$ obtained across the experiments are computed and plotted, respectively the solid line and the dot-dashed line. The dotted line represents the ideal situation, corresponding to $\hat{\rho} = \rho$.

The left panel shows that the SSR estimation is stable around 0.90 with a very low variability and therefore almost unconditional to the simulated autoregressive disturbance. Then, estimating ρ with SSR practically corresponds to constrain the parameter in the interval $(0.90, 0.95)$. Conversely, both ML and CL give estimates which are positively related to ρ with a very large variability in the experiments. In particular for $\rho < 0.50$ ML obtains several disaggregations with negative values of $\hat{\rho}$. A reduction of the standard error can be noticed for $\rho > 0.80$. An elevate standard error can either be seen for CL but no solution with $\hat{\rho} < 0$ is actually obtained. The accuracy and stability of the estimates slightly improve for $\rho > 0.50$.

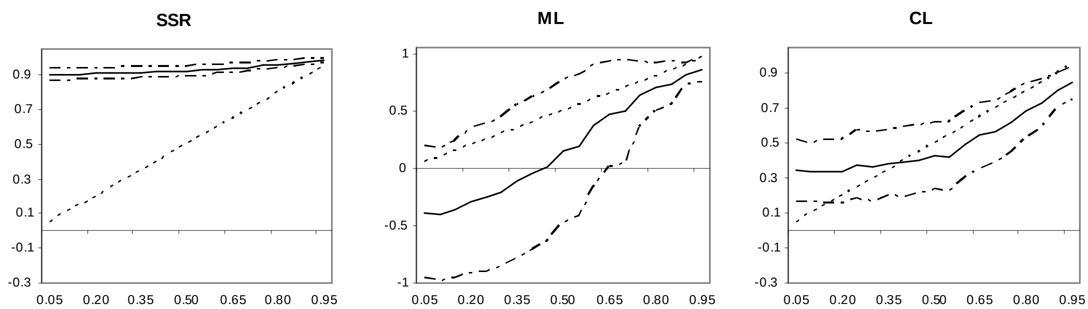

Figure 3: Average and standard deviation of $\widehat{\rho}$ for different values of ρ.

4.1.3 The disaggregated series

The performances of the estimation methods are compared by evaluating the relative accuracy of the estimated disaggregations in reproducing the simulated series, in both in-sample (100 quarters) and out-of-sample (4 quarters) periods.

The in-sample comparison among the methods has been made either for raw and seasonal adjusted series. We report in Table 6 the RMSPE on the levels (L) of the raw and seasonal adjusted series and the RMSE on the growth rates (G1) of the seasonal adjusted series. These series are also evaluated through an analysis quarter by quarter: the table shows the RMSE of growth rates relative to the first quarters (G1Q1), in order to evaluate the ability of the different methods to avoid spurious jumps between the fourth quarter of one year and the first quarter of the next.

Considering I1, larger values of ρ improve the accuracy of the disaggregated series: we can note that the average statistics (on levels and growth rates) are more than twice from $\rho = 0.1$ to $\rho = 0.9$. The statistics shown by SSR and CL are equivalent for any value of ρ. Instead, those of ML are always larger for low values of ρ with higher standard deviations; for $\rho = 0.9$ the results become indistinguishable from those of SSR and CL. The RMSE on the first quarters reveals some problems of ML for low values of ρ (for $\rho = 0.1$, 8.39% of ML against 5.06% of CL). This implies a larger presence of jumps in the estimated series by ML, an unpleasant property in the distribution of a time series.

Similar comments can be made for I2 and I3. No difference arises among the methods when $\rho = 0.9$ while, if $\rho < 0.9$, a greater ability of CL and SSR can be observed. The statistics for I3 are the lowest: this can be explained by the simple structure of the model, because of the absence of an integrated component. Comparing the statistics for raw and seasonal adjusted series, any effect in the performance seems to be due to the seasonal component.

In brief, the in-sample results show the same performances for $\rho > 0.9$ while, if $\rho < 0.9$, CL and SSR outperform ML. This statement is confirmed by Table 7, which shows the percentage of times with the best RMSPEL for each method. Slight changes of this proportion can be noticed in the scenarios. The percentage of successes for SSR decreases as ρ increases while the opposite is true for ML; any clear relationship is noticed with the three models considered. The percentage with the best RMSPEL for ML varies from 6.2% ($\rho = 0.15$) to 25.4% ($\rho = 0.95$). The percentage relative to SSR is always greater than 50% for $\rho \leq 0.55$ and even when $\rho > 0.55$ SSR largely outperforms the other methods. The percentage with the best RMSPEL for CL is around 30% and does not show any clear relationship with ρ.

Combining the results from Table 6 and 7 we would give our preference to SSR, characterized by a low percentage of non-admissible solutions and a better adequacy of the estimated series.

The out-of-sample performance is assessed for both raw and seasonal adjusted series by computing the percentage error of the annual extrapolated level (derived as the sum of the four extrapolated quarters). The ME and RMSE of growth rates for the extrapolated quarters are also computed. The former statistics are needed to evaluate the accuracy of the annualized forecast on the basis of the indicator series, while analysing the errors in terms of growth rates we try to evaluate the ability of the different methods to reproduce the short-term information of the indicator.

In Table 8 the forecasting results are presented. The forecasting accuracy differs significantly for different indicator models. We notice a better quality of the extrapolated figures with I3, while the worst results are obtained with I2. ML is the most accurate estimation method when the goal is to estimate the annual value of the objective series, while the quarterly movements are often replicated with better accuracy by SSR and CL. For example, in the scenario I2 and $\rho = 0.1$ ML shows a mean absolute percentage error of 3.85% while CL and SSR have 4.06% and 5.34% respectively. On the contrary, the RMSE on the quarterly growth rates of ML is sensibly higher (14.17% against 10.77% of CL and 11.66% of SSR). A further interesting result is that all the estimation methods over-estimate the true level of the quarterly series for the scenario I2, especially for low values of ρ.

4.2 Exercise $E2$: a comparison of alternative regression-based techniques

4.2.1 The admissibility of the solutions

Table 9 shows the percentage of admissible solutions for five disaggregation approaches (CL, FER, LIT, LIT snc and ADL(1,0)) and two estimation methods (SSR and ML). Because of the large number of the scenarios simulated in exercise $E2$, results are presented aggregating them by indicator model and by disturbance model, whereas the last column refers to all the scenarios.

The table contains percentages both in boldface and in normal font. The percentages printed in bold type show the proportion of series for which the disaggregation approach indicated in the first column fulfil the admissibility conditions. On the contrary, the percentages printed in normal font refer to the proportion of series for which *both* the approaches indicated in the first column fulfil the admissibility conditions. In other words, they show the size of the series subsets for which two approaches give admissible solutions simultaneously. As it will be seen later, this helps the interpretation of the results concerning the disaggregation performances and the comparison among the various approaches. Therefore we do not describe them in this section and we only consider the results printed in bold type.

From the percentages in the last column, it can be seen that the Fernández solution always fulfils the admissibility conditions, as it does not require the estimation of any autoregressive parameter. For CL the percentage of admissible solutions exceeds 85% and it depends on the estimation method: 85.8% for SSR and 98.4% for ML[5]. An opposite result comes from LIT: the percentage is 98.4% for SSR, drops to 55% for ML and gets worse by estimating the starting condition (49%). Similarly, ADL(1,0) ssr (91.5%) outperforms ADL(1,0) ml (78.9%).

[5]The result is in contrast with that found in the previous exercise because in this exercise we extend the admissibility interval of $\hat{\rho}$ to [-0.999,0.999].

This regularity is confirmed by the percentages presented in boldface in the columns 2-8, where the results are aggregated by indicator model. This means that the ARIMA models used to generate the indicator series, in particular their integration order and their seasonality, do not influence the number of admissible solutions (except for ADL(1,0) ssr).

From the aggregation by disturbance model (columns 9-15, figures in boldface) it is seen that the percentage of admissible solutions depends upon the ARIMA model and the estimation method. In fact, for ML, the larger ρ, ϕ and the integration order, the fewer the solutions to be discarded. An opposite regularity is detected for SSR.

4.2.2 The estimation of parameters

As we stressed in Section 3, the use of fixed parameters to generate the disturbance series allows us to assess the estimation accuracy. Table 9 shows the average bias and the standard error of the estimated coefficients $\hat{\beta}$, $\hat{\rho}$ (for CL) and $\hat{\phi}$ (for LIT). These statistics are computed when the temporal disaggregation fulfils the admissibility conditions.

As regards β, CL approach gives the best estimates. In particular the bias of the ML estimates are larger than the SSR estimates, but the former are less unstable than the latter. For LIT approach the ML method reduces the bias and the standard error of the SSR estimates; the estimation of the starting condition does not improve the ML results (the discrepancy between LIT ml and LIT nsc is negligible).

As far as the estimation of ρ is concerned (see the upper left corner in the second panel of Table 10), the results are remarkably affected by the estimation method. Firstly, SSR overestimates the generated value of ρ, even when $\rho = 0.9$ (this confirms the results of exercise $E1$), while ML underestimates the generated ρ. Secondly, the standard error of the estimates decreases for larger values of ρ. With regard to ϕ (see the lower right corner of the table), LIT ssr results are analogous to those ones achieved by CL ssr and do not need further discussion. LIT ml performs very well, particularly for large values of the generated parameter, and better than LIT nsc.

4.2.3 The disaggregated series

The accuracy of the disaggregation techniques can be evaluated through the statistics shown in tables 11-14. In order to better understand the properties of the disaggregation methods, the results are showed by indicator and disturbance models. The results by different R^2, on the contrary, are not considered, as they confirm our expectations: the larger the coefficient of determination, the better the disaggregated series. The tables also distinguish in-sample and out-of-sample periods; in the former we show the average (first line) and standard error (second line, italic font) of RMSPEL across the experiments, while in the latter we report the same aggregated measures of the annual absolute percentage error (APEL).

Following the same reasoning introduced in Section 4.2.1, we arrange the data in a way that fair comparisons of the relative performances of the methods can be made. The tables include eight sub-tables, one for each method shown in the first row (in boldface). Each sub-table shows the statistics relative to the method denoted in the first column, computed only considering its admissible solutions (see Table 9). The next rows show the same statistics for the other methods, but calculated on the subset of solutions for which the method in the first row have provided admissible results. Clearly, the number of experiments considered for these other methods can be at most the same of those obtained by the method in the first row. Consider the following examples which make clear the understanding of figures across the tables. From Table 11 we notice that CL ml, with 97.7% of admissible solutions, obtains a global average RMSPEL of 7.6 for I1 (see the panel in the upper right corner of the table) but produces an higher statistic, 8.5 (see the panel in the upper left corner of the table), when only the common solutions with CL ssr (82.4%) are selected. At the same time, from Table 13 we see that CL ml improves its accuracy for C1 when it is crossed with ADL(1,0) ml (from 16.2 to 13.6, with 96.6% and 66.1% of admissible results respectively).

By crossing the admissible solutions we are able to compare each method with the others on a common set of experiments. In this way we try to help those methods (like FER) which provide acceptable disaggregations to experiments in which other methods normally fail. Obviously, when crossed with FER the statistics of the other methods do not change. But we are also able to discover, for instance, that the global accuracy of FER for I2 (6.0) is much better when only the common solutions with LIT nsc (2.8, with 48.3% of admissible results) are considered.

Unfortunately for the reader, there is a huge amount of figures in the following tables. This makes rather complicated to have an immediate idea on the relative positions of the methods. An attempt to rank the methods by considering both accuracy measures and percentages of admissible results is illustrated at the end of this section. Now we instead try to highlight some interesting aspects from the results in Tables 11-14.

The eight sub-tables of Table 11 show the in-sample accuracy of the method in the first row by different DGPs for indicator models, compared to those of the other methods in the common set of experiments.

The scenarios I1 and I2 are those for which the disaggregation methods meet major difficulties, in both raw and seasonal adjusted versions. The reason is probably connected with the inclusion of a second-order integrated component in the indicator series, while I3 and I4 both contain a first-order integrated process. An interesting result can be noted for I3: the static solutions obtain the best accuracy for this model among the seasonal series while, on the contrary, a higher level of RMSPEL is provided by ADL(1,0).

CL ssr improves over CL ml for all scenarios. A lower average level of RMSPEL is always achieved by the SSR estimation of ρ; moreover, the volatility obtained by the ML estimation is almost twice. Opposite considerations apply for the Litterman solution:

estimating by maximum likelihood we always achieve better results than SSR. The dynamic solution ADL(1,0) (both SSR and ML) never outperforms the results given by the static solutions.

Only LIT nsc and LIT ml improve over the results by FER (for example, 2.9 and 3.2 against 5.9 for I1). However, we continue to stress that these statistics are based on a different number of experiments because of the non-admissible results (48.9% and 55.1% for the same example). The comparison of the Fernández solution is better achieved by looking at the relative accuracy on the common solutions with the other methods. Using this perspective we find that FER is almost always in the first positions. If we look at the tables relative to LIT nsc and LIT ml, we note that FER improves its accuracy obtaining roughly the same performance. It is also clear that the common solutions to LIT nsr or LIT ml are those for which the static methods derive very similar results; this view makes clear why the good performance of the Litterman solution is only apparent.

Table 13 analyses the results by different DGPs for disturbance series. The scenarios C1 and C5 are those in which the disaggregation techniques have the worse results: the level of RMSPEL is sensibly reduced when the disturbance series contain an integrated process. This evidence confirms the results found in exercise $E1$.

To synthesize the results, we try to order the methods considering both accuracy of disaggregation and capacity to give admissible results. Firstly, we assign the ranks (in ascending order) to the methods in each table. Then, we take the rank of the method placed in the first row. The resulting list does not take account of the different number of solutions on which the statistics are calculated. We want now to produce a modified classification in which the methods with lower number of admissible results are penalized. Denote the initial rank of a generic method by r. This is adjusted through the following formula

$$r^a = r + \left(2 - \frac{AS}{TS}\right)^3 - 1 \tag{19}$$

where AS is the number of admissible solutions and TS is the total number of experiments. The greater is the number of non-admissible results, the more penalized is the method. When $AS = TS$, no adjustment is done. If $AS = 0$, the maximum penalization (7) is added to the original rank. The final order is achieved by sorting the methods by r^a.

Table 15 shows the adjusted ranking r_a by indicator models, for both distribution and extrapolation periods. We remind that each line represents the adjusted ranking of each method in the corresponding sub-table; this explains why the same rank is associated to different methods. The simple average of the ranks is shown in the last column of the tables; the methods are listed in ascending order by this average. The technique by Fernández is the best method in the interpolation period (1.3); for 6 out of 7 indicator models FER provides the most accurate distributions. CL ssr is in the second position

(2.1), while LIT nsc (2.3) and LIT ml (2.7) are surely the most penalized by the adjustment for non-admissible disaggregations. CL ml is almost always in the last place (7.1), but the worst result is provided by ADL(1,1) ml (7.3).

In spite of the bad position in the distribution problem, CL ml results as the the best method concerning the accuracy of the extrapolated annual figures. Furthermore, FER shows a much lower performance (5.0), surpassed by LIT nsc (1.4), LIT ml (2.4) and CL ssr (4.1).

From Table 16 we can see the same tables organized by disturbance models. This analysis shows CL ssr in the first place (2.0), for its better accuracy with AR(1) disturbances, while FER stays in the second position (2.9). The two Chow-Lin solutions occupy the first places in extrapolation, with CL ml the best one when AR(1) model is used for the disturbance series. FER reaches the second place when the simulated disturbance is I(1), coherent with the theoretical assumption of the method. Similarly, LIT nsc is the best method for L9 in both distribution and extrapolation cases.

5 Conclusions

It is not simple to derive general conclusions from simulation exercises. We acknowledge that results might differ changing the simulation design, like the length of series or the models for indicators/disturbances. Nevertheless, some remarks can be made about the properties of the methods we have tested. In particular, we refer to those properties desirable for the needs of a data producer: existence of admissible solutions, estimation accuracy of the parameters and goodness of fit with respect to the objective series.

In the first exercise we compare three estimation approaches for the autoregressive parameter assumed in the Chow-Lin solution. In the scenarios considered the maximum likelihood procedure (ML) and the method suggested by Chow and Lin (CL) show a larger amount of non-admissible solutions than the minimization of the sum of squared residuals (SSR). This is particularly true for low values of the AR parameter. However, it is important to stress that the AR parameter rarely assumes low values with real time series and that the percentage of successes with ML and CL should improve with real-world variables.

Considering the admissible solutions, CL and ML provide better estimates of the regression coefficients than SSR. In general the estimates improve for decreasing values of ρ. Opposite considerations hold for the estimation of ρ. Both ML and CL give better results as the simulated ρ increases; they turn out to be rather volatile with respect to SSR. In particular, for $\rho < 0.50$ ML is likely to provide negative estimates of ρ. The estimates of ρ by SSR are approximately around $0.90 - 0.95$ with little volatility and almost independently to the true value of the AR parameter. Even though this guarantees a good reliability of the estimated series, it is not theoretically correct as the parameter ρ is almost always overestimated.

Finally, the estimated series obtained by SSR are generally the closest one to simulated series in the in-sample period while ML obtain slight improvements over the other estimation methods in the extrapolation case. It must be considered that for high values of ρ the results of the methods tend to coincide.

In the second exercise we extend the comparison to other proposals based on the Chow-Lin formulation of the disaggregation problem. Considering either admissibility of results and accuracy of disaggregation, we found that the Fernández approach gives the most satisfactory results in the in-sample analysis, while it yields intermediate results in the out-of-sample analysis. As far as the forecasting accuracy is concerned, it is the Chow-Lin solution with maximum likelihood estimation of the autoregressive parameter which outperforms the other methods. The admissible results for the Litterman proposal are very accurate, but the number of solutions with $\phi = -0.999$ is too high. The results from the dynamic solutions do not compete with those from the static techniques, but this is certainly connected with the fact that the simulation model used in the experiments is static.

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Table 4: Percentage of non-admissible solutions for different scenarios.

	condition	I1			I2			I3		
		$\rho = 0.1$	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9
CL	not invertible	62.2	28.2	0.0	63.2	29.2	0.4	62.8	25.8	0.0
ML	$\widehat{\rho} < -0.9$	32.0	27.0	0.2	31.8	26.8	0.2	25.0	24.0	0.4
SSR	$\widehat{\rho} = 0.999$	2.6	2.8	8.2	2.6	2.2	4.8	0.0	0.2	8.8

Table 5: Average bias and error (%) of the estimated regression coefficients.

$\rho = 0.1$												
	I1				I2				I3			
	$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$	
	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error
CL	0.59	4.99	-0.20	1.38	0.70	5.53	-0.11	1.34	0.08	1.34	-0.08	1.88
ML	-0.01	4.81	-0.07	1.35	-0.78	6.35	0.13	1.37	-0.10	1.26	0.14	1.84
SSR	0.25	7.86	-0.05	2.67	-0.48	10.97	0.41	2.84	-0.32	2.58	0.39	3.66

$\rho = 0.5$												
	I1				I2				I3			
	$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$	
	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error
CL	-0.59	6.90	-0.01	2.20	0.60	9.53	-0.10	2.13	-0.18	2.03	0.22	2.86
ML	-1.06	7.82	0.04	2.29	0.01	9.26	-0.06	2.09	-0.28	2.06	0.42	2.95
SSR	-1.19	11.73	0.05	3.88	-0.46	15.26	0.28	3.59	-0.24	3.50	0.42	5.0

$\rho = 0.9$												
	I1				I2				I3			
	$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$		$\widehat{\alpha}$		$\widehat{\beta}$	
	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error
CL	0.08	17.09	-0.25	4.92	1.59	21.70	-0.12	4.48	0.26	2.67	-0.34	3.82
ML	0.11	17.07	-0.26	4.89	1.41	21.72	-0.09	4.47	0.24	2.64	-0.31	3.77
SSR	-1.22	21.53	0.07	6.34	-0.94	28.06	0.42	5.79	0.23	2.74	-0.29	3.79

Table 6: Performance measures in the in-sample period: average error and standard deviation of RMSE (%).

	I1				I2				I3			
	raw	seasonal adjusted			raw	seasonal adjusted			raw	seasonal adjusted		
	L	L	G1	G1Q1	L	L	G1	G1Q1	L	L	G1	G1Q1
$\rho = 0.1$												
CL	3.74	3.71	5.15	5.06	4.63	4.62	5.96	5.75	0.90	0.64	0.91	0.89
	(1.87)	(1.89)	(2.49)	(2.64)	(3.94)	(3.94)	(3.42)	(3.81)	(0.21)	(0.17)	(0.25)	(0.26)
ML	5.0	4.96	6.45	8.39	6.36	6.36	7.97	10.65	1.18	0.84	1.14	1.40
	(2.94)	(2.96)	(3.53)	(6.02)	(4.66)	(4.69)	(4.94)	(11.34)	(0.40)	(0.30)	(0.34)	(0.65)
SSR	3.81	3.77	5.19	5.14	4.67	4.65	6.09	6.04	0.94	0.66	0.94	0.93
	(1.94)	(1.97)	(2.52)	(2.70)	(3.29)	(3.32)	(3.21)	(3.64)	(0.23)	(0.17)	(0.25)	(0.27)
$\rho = 0.5$												
CL	3.02	2.99	4.25	3.63	3.56	3.55	4.91	4.24	0.73	0.52	0.76	0.66
	(1.56)	(1.59)	(2.11)	(1.86)	(2.09)	(2.12)	(2.49)	(2.39)	(0.17)	(0.13)	(0.20)	(0.19)
ML	4.02	3.98	5.35	6.49	4.92	4.90	6.46	8.07	1.02	0.73	1.00	1.17
	(3.03)	(3.04)	(3.56)	(7.27)	(3.94)	(3.98)	(4.59)	(10.64)	(0.57)	(0.42)	(0.49)	(0.96)
SSR	3.04	3.01	4.29	3.62	3.63	3.62	4.99	4.30	0.79	0.53	0.78	0.67
	(1.54)	(1.58)	(2.14)	(1.84)	(2.15)	(2.18)	(2.56)	(2.45)	(0.24)	(0.14)	(0.21)	(0.19)
$\rho = 0.9$												
CL	1.52	1.50	2.19	1.71	1.84	1.83	2.58	2.00	0.43	0.26	0.40	0.32
	(0.86)	(0.88)	(1.23)	(1.00)	(1.28)	(1.30)	(1.58)	(1.21)	(0.18)	(0.09)	(0.13)	(0.11)
ML	1.52	1.50	2.19	1.72	1.86	1.84	2.60	2.04	0.42	0.26	0.40	0.32
	(0.86)	(0.88)	(1.23)	(1.01)	(1.31)	(1.33)	(1.60)	(1.39)	(0.18)	(0.08)	(0.13)	(0.11)
SSR	1.53	1.49	2.18	1.71	1.85	1.83	2.58	2.00	0.43	0.26	0.40	0.32
	(0.86)	(0.88)	(1.22)	(0.99)	(1.32)	(1.34)	(1.59)	(1.21)	(0.20)	(0.09)	(0.13)	(0.11)

Table 7: Percentage of times with the best RMSPEL: in-sample period.

I1										
	$\rho = 0.05$	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
CL	22.8	24.4	22.0	25.2	31.4	30.0	27.4	33.6	31.4	27.6
ML	10.8	8.2	9.4	11.2	11.2	13.4	20.2	21.0	22.4	22.0
SSR	66.4	67.4	68.6	63.6	57.4	56.6	52.4	45.4	46.2	50.4

I2										
	$\rho = 0.05$	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
CL	23.0	26.6	23.0	27.4	27.6	25.8	25.4	30.6	31.8	26.6
ML	6.8	6.2	9.2	9.6	12.6	16.0	16.4	18.6	20.0	22.8
SSR	70.2	67.2	67.8	63.0	59.8	58.2	58.2	50.8	48.2	50.6

I3										
	$\rho = 0.05$	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
CL	24.4	23.4	27.0	30.4	29.4	29.0	30.4	29.8	29.0	34.2
ML	9.6	9.2	11.8	11.0	17.8	19.6	25.2	24.0	23.8	25.4
SSR	66.0	67.4	61.2	58.6	52.8	51.4	44.4	46.2	47.2	40.4

Table 8: Performance measures in the out-of-sample period average and standard deviation of some statistics (%).

$\rho = 0.1$

	I1				I2				I3			
	raw	seasonal adjusted			raw	seasonal adjusted			raw	seasonal adjusted		
	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1
CL	2.78	2.76	-0.60	7.12	4.06	4.07	-1.34	10.77	0.45	0.32	0.01	0.91
	(0.04)	(0.04)	(3.15)	(8.76)	(0.08)	(0.07)	(5.86)	(16.24)	(0.00)	(0.00)	(0.25)	(0.41)
ML	3.02	3.01	0.22	8.77	3.85	3.84	-1.32	14.17	0.47	0.34	0.01	1.08
	(0.05)	(0.05)	(4.19)	(11.82)	(0.08)	(0.08)	(9.87)	(25.83)	(0.01)	(0.00)	(0.25)	(0.59)
SSR	4.05	4.04	-0.37	7.62	5.34	5.26	-1.97	11.66	0.65	0.47	0.01	0.93
	(0.07)	(0.07)	(3.44)	(9.03)	(0.10)	(0.10)	(8.67)	(21.22)	(0.01)	(0.01)	(0.26)	(0.43)

$\rho = 0.5$

	I1				I2				I3			
	raw	seasonal adjusted			raw	seasonal adjusted			raw	seasonal adjusted		
	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1
CL	4.07	4.04	-0.20	6.02	6.26	6.20	-1.27	9.29	0.60	0.44	0.00	0.70
	(0.07)	(0.07)	(2.80)	(7.24)	(0.16)	(0.16)	(8.82)	(20.40	(0.01)	(0.01)	(0.25)	(0.32)
ML	3.65	3.62	0.25	6.65	6.05	5.96	-0.61	10.91	0.62	0.45	0.01	0.91
	(0.06)	(0.06)	(4.54)	(11.14)	(0.15)	(0.15)	(9.58)	(23.51	(0.01)	(0.01)	(0.26)	(0.65)
SSR	4.57	4.53	-0.17	5.97	7.30	7.19	-1.34	9.30	0.81	0.58	0.00	0.74
	(0.09)	(0.08)	(3.33)	(7.02)	(0.17)	(0.17)	(8.01)	(18.68	(0.01)	(0.01)	(0.27)	(0.34)

$\rho = 0.9$

	I1				I2				I3			
	raw	seasonal adjusted			raw	seasonal adjusted			raw	seasonal adjusted		
	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1	apeL	apeL	me1	rmse1
CL	3.95	3.93	-0.11	3.11	5.67	5.64	-0.16	4.37	0.60	0.44	0.01	0.37
	(0.07)	(0.07)	(2.54)	(4.05)	(0.11)	(0.11)	(3.45)	(6.23)	(0.01)	(0.01)	(0.18)	(0.20)
ML	3.93	3.91	-0.11	3.11	5.63	5.59	-0.17	4.36	0.59	0.43	0.01	0.37
	(0.07)	(0.07)	(2.53)	(4.06)	(0.11)	(0.11)	(3.44)	(6.24)	(0.01)	(0.01)	(0.17)	(0.19)
SSR	3.89	3.84	-0.18	3.19	5.95	5.84	-0.48	4.53	0.65	0.46	0.00	0.38
	(0.07)	(0.07)	(2.57)	(4.12)	(0.12)	(0.12)	(4.20)	(6.71)	(0.01)	(0.01)	(0.19)	(0.20)

Table 9: Percentages of admissible solutions.

	by indicator model							by disturbance model							Total
	I1	**I2**	**I3**	**I1sa**	**I2sa**	**I3sa**	**I4**	**C1**	**C5**	**C9**	**F**	**L1**	**L5**	**L9**	
CL ssr	**84.7**	**86.1**	**86.3**	**84.7**	**86.2**	**86.3**	**86.3**	**98.3**	**98.4**	**93.0**	**92.0**	**91.8**	**86.2**	**40.9**	**85.8**
CL ml	**97.7**	**97.2**	**99.4**	**97.8**	**97.2**	**100.0**	**99.7**	**96.6**	**92.7**	**99.7**	**100.0**	**100.0**	**100.0**	**100.0**	**98.4**
FER	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
LIT ssr	**97.5**	**97.6**	**99.3**	**97.8**	**97.7**	**99.3**	**99.4**	**99.5**	**98.3**	**98.8**	**99.4**	**99.1**	**98.8**	**94.7**	**98.4**
LIT ml	**55.1**	**54.1**	**55.7**	**55.1**	**54.1**	**55.7**	**54.9**	**1.8**	**4.0**	**47.0**	**70.6**	**71.2**	**90.3**	**99.9**	**55.0**
LIT nsc	**48.9**	**48.3**	**50.1**	**48.9**	**48.3**	**50.0**	**48.7**	**1.0**	**2.1**	**32.0**	**61.4**	**61.8**	**85.0**	**99.9**	**49.0**
ADL(1,0) ssr	**87.7**	**87.5**	**96.4**	**87.8**	**87.5**	**98.7**	**95.2**	**99.8**	**99.4**	**96.4**	**91.0**	**90.0**	**86.6**	**77.7**	**91.5**
ADL(1,0) ml	**78.8**	**78.0**	**77.7**	**78.9**	**78.2**	**80.5**	**80.4**	**66.7**	**60.6**	**81.6**	**84.1**	**85.0**	**87.5**	**87.0**	**78.9**
CL ssr - CL ml	82.4	83.4	85.7	82.6	83.4	86.2	86.0	95.0	91.2	92.6	92.0	91.8	86.2	40.9	84.2
CL ssr - FER	84.7	86.1	86.3	84.7	86.2	86.3	86.3	98.3	98.4	93.0	92.0	91.8	86.2	40.9	85.8
CL ssr - LIT ssr	82.7	84.3	86.1	82.9	84.4	86.1	86.1	97.8	96.7	91.8	91.5	90.9	85.3	38.7	84.7
CL ssr - LIT ml	41.4	41.8	42.6	41.5	41.8	42.6	41.8	1.4	3.6	43.0	63.8	63.9	76.9	40.9	41.9
CL ssr - LIT nsc	35.6	36.3	37.1	35.6	36.3	37.1	35.9	0.5	1.8	28.3	55.1	55.5	71.9	40.9	36.3
CL ssr - ADL(1,0) ssr	77.0	77.8	83.8	77.1	77.9	85.3	82.8	98.1	97.8	89.8	84.6	83.7	75.8	32.0	80.3
CL ssr - ADL(1,0) ml	65.7	66.2	68.1	65.9	66.4	71.7	70.8	66.0	60.0	77.0	78.0	78.6	76.5	38.7	67.8
CL ml - FER	97.7	97.2	99.4	97.8	97.2	100.0	99.7	96.6	92.7	99.7	100.0	100.0	100.0	100.0	98.4
CL ml - LIT ssr	95.4	94.9	98.7	95.7	94.9	99.3	99.1	96.1	91.5	98.4	99.4	99.0	98.8	94.7	96.9
CL ml - LIT ml	55.1	54.1	55.7	55.1	54.0	55.7	54.9	1.7	3.9	47.0	70.6	71.2	90.3	99.9	54.9
CL ml - LIT nsc	48.9	48.3	50.1	48.9	48.3	50.0	48.7	0.9	2.1	32.0	61.4	61.8	85.0	99.9	49.0
CL ml - ADL(1,0) ssr	85.4	84.7	95.8	85.6	84.7	98.7	94.9	96.4	92.2	96.0	90.9	90.0	86.6	77.7	90.0
CL ml - ADL(1,0) ml	78.3	77.4	77.4	78.4	77.6	80.5	80.3	66.1	58.7	81.6	84.1	85.0	87.5	87.0	78.6
FER - LIT ssr	97.5	97.6	99.3	97.8	97.7	99.3	99.4	99.5	98.3	98.8	99.4	99.1	98.8	94.7	98.4
FER - LIT ml	55.1	54.1	55.7	55.1	54.1	55.7	54.9	1.8	4.0	47.0	70.6	71.2	90.3	99.9	55.0
FER - LIT nsc	48.9	48.3	50.1	48.9	48.3	50.0	48.7	1.0	2.1	32.0	61.4	61.8	85.0	99.9	49.0
FER - ADL(1,0) ssr	87.7	87.5	96.4	87.8	87.5	98.7	95.2	99.8	99.4	96.4	91.0	90.0	86.6	77.7	91.5
FER - ADL(1,0) ml	78.8	78.0	77.7	78.9	78.2	80.5	80.4	66.7	60.6	81.6	84.1	85.0	87.5	87.0	78.9
LIT ssr - LIT ml	53.6	52.6	55.0	53.6	52.5	55.1	54.3	1.8	3.9	46.4	70.1	70.6	89.3	94.6	53.8
LIT ssr - LIT nsc	47.4	46.8	49.4	47.5	46.8	49.4	48.1	1.0	2.1	31.6	61.0	61.2	84.0	94.6	47.9
LIT ssr - ADL(1,0) ssr	85.9	85.7	95.7	86.3	85.8	98.1	94.7	99.2	97.8	95.3	90.5	89.2	85.8	74.5	90.3
LIT ssr - ADL(1,0) ml	76.9	76.1	77.2	77.0	76.3	80.1	80.0	66.6	60.1	80.5	83.6	84.2	86.4	82.3	77.7
LIT ml - LIT nsc	48.6	48.2	50.0	48.7	48.2	49.9	48.7	0.8	1.9	31.7	61.2	61.8	85.0	99.9	48.9
LIT ml - ADL(1,0) ssr	43.8	42.6	52.7	43.8	42.6	54.8	50.9	1.8	4.0	44.8	62.7	62.8	77.6	77.6	47.3
LIT ml - ADL(1,0) ml	51.9	50.8	45.6	51.6	50.7	44.0	45.2	1.5	3.4	41.5	62.5	63.6	80.4	86.9	48.6
LIT nsc - ADL(1,0) ssr	38.0	37.2	47.2	38.0	37.2	49.2	44.9	1.0	2.1	30.4	54.3	53.9	72.4	77.6	41.7
LIT nsc - ADL(1,0) ml	46.0	45.8	41.2	45.8	45.8	39.6	40.3	0.6	1.8	28.6	54.9	55.6	76.1	86.9	43.5
ADL ssr - ADL(1,0) ml	67.5	66.6	74.6	67.8	66.8	79.7	77.1	66.6	60.4	78.8	76.5	76.4	75.5	65.9	71.4

Table 10: Average bias and standard error of the estimated coefficients.

	β						
	C1	**C5**	**C9**	**F**	**L1**	**L5**	**L9**
CL ssr	-0.002	0.001	0.002	-	-	-	-
s.e.	*0.286*	*0.342*	*0.365*	-	-	-	-
CL ml	0.000	-0.002	0.007	-	-	-	-
s.e.	*0.161*	*0.229*	*0.321*	-	-	-	-
FER	-	-	-	-0.004	-	-	-
s.e.	-	-	-	*0.378*	-	-	-
LIT ssr	-	-	-	-	0.044	-0.001	-0.012
s.e.	-	-	-	-	*2.342*	*2.029*	*0.854*
LIT ml	-	-	-	-	-0.013	-0.004	-0.003
s.e.	-	-	-	-	*0.436*	*0.453*	*0.505*
LIT ml nsc	-	-	-	-	-0.012	-0.004	-0.005
s.e.	-	-	-	-	*0.412*	*0.431*	*0.485*
	ρ (for CL) and ϕ (for LIT)						
	C1	**C5**	**C9**	**F**	**L1**	**L5**	**L9**
CL ssr	0.808	0.427	0.073	-	-	-	-
s.e.	*0.809*	*0.428*	*0.075*	-	-	-	-
CL ml	-0.602	-0.562	-0.089	-	-	-	-
s.e.	*0.839*	*0.906*	*0.183*	-	-	-	-
LIT ssr	-	-	-	-	0.816	0.431	0.074
s.e.	-	-	-	-	*0.817*	*0.432*	*0.076*
LIT ml	-	-	-	-	0.224	-0.015	-0.040
s.e.	-	-	-	-	*0.450*	*0.262*	*0.090*
LIT ml nsc	-	-	-	-	0.158	-0.096	-0.047
s.e.	-	-	-	-	*0.450*	*0.360*	*0.103*

Table 11: In-sample period: RMSPEL for different DGPs for indicators.

	I1	I2	I3	I1sa	I2sa	I3sa	I4
CL ssr	**6.3**	**6.7**	**4.8**	**6.1**	**6.6**	**2.2**	**3.4**
s.d.	**5.2**	**5.6**	**4.1**	**5.3**	**5.6**	**1.9**	**2.9**
CL ml	8.5	8.7	6.0	8.3	8.6	3.3	4.9
s.d.	*9.6*	*9.8*	*6.7*	*9.6*	*9.8*	*4.6*	*6.4*
FER	6.4	6.7	4.8	6.1	6.6	2.2	3.4
s.d.	*5.3*	*5.6*	*4.2*	*5.3*	*5.6*	*1.9*	*2.9*
LIT ssr	7.7	7.3	5.2	6.3	6.7	2.3	3.5
s.d.	*6.4*	*6.0*	*4.8*	*5.4*	*5.7*	*2.0*	*3.0*
LIT ml	3.4	3.5	2.9	3.2	3.4	1.2	1.8
s.d.	*2.7*	*2.9*	*2.7*	*2.6*	*2.9*	*1.0*	*1.4*
LIT nsc	3.2	3.2	2.7	2.9	3.1	1.1	1.6
s.d.	*2.5*	*2.6*	*2.5*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	7.5	7.5	10.0	6.6	7.1	3.7	5.0
s.d.	*5.0*	*5.5*	*3.2*	*5.2*	*5.7*	*1.6*	*2.3*
ADL(1,0) ml	7.1	6.9	8.8	6.2	6.5	3.5	4.8
s.d.	*7.0*	*7.1*	*5.3*	*6.8*	*7.0*	*3.7*	*4.4*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
CL ml	**7.6**	**7.9**	**5.4**	**7.4**	**7.8**	**2.9**	**4.3**
s.d.	**9.3**	**9.5**	**6.5**	**9.3**	**9.5**	**4.4**	**6.1**
CL ssr	6.1	6.3	4.7	5.9	6.3	2.2	3.3
s.d.	*5.1*	*5.3*	*4.1*	*5.1*	*5.4*	*1.9*	*2.9*
FER	5.6	5.8	4.3	5.4	5.7	2.0	3.0
s.d.	*5.0*	*5.3*	*4.1*	*5.0*	*5.3*	*1.9*	*2.8*
LIT ssr	7.0	6.5	4.6	5.6	5.9	2.0	3.1
s.d.	*6.2*	*5.7*	*4.6*	*5.1*	*5.3*	*2.0*	*2.9*
LIT ml	3.2	3.2	2.4	2.8	3.0	1.0	1.5
s.d.	*2.7*	*2.8*	*2.6*	*2.6*	*2.8*	*0.9*	*1.4*
LIT nsc	2.9	2.9	2.2	2.6	2.8	0.9	1.3
s.d.	*2.6*	*2.6*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	7.0	6.8	9.9	6.0	6.4	3.6	4.8
s.d.	*4.8*	*5.2*	*3.3*	*5.0*	*5.3*	*1.5*	*2.2*
ADL(1,0) ml	6.5	6.2	8.8	5.5	5.7	3.4	4.6
s.d.	*6.6*	*6.6*	*5.2*	*6.4*	*6.6*	*3.5*	*4.2*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
FER	**5.9**	**6.1**	**4.3**	**5.6**	**6.0**	**2.0**	**3.0**
s.d.	**5.2**	**5.5**	**4.1**	**5.2**	**5.6**	**1.9**	**2.8**
CL ssr	6.3	6.7	4.8	6.1	6.6	2.2	3.4
s.d.	*5.2*	*5.6*	*4.1*	*5.3*	*5.6*	*1.9*	*2.9*
CL ml	7.6	7.9	5.4	7.4	7.8	2.9	4.3
s.d.	*9.3*	*9.5*	*6.5*	*9.3*	*9.5*	*4.4*	*6.1*
LIT ssr	7.2	6.8	4.7	5.8	6.2	2.0	3.1
s.d.	*6.4*	*6.0*	*4.7*	*5.3*	*5.6*	*2.0*	*3.0*
LIT ml	3.2	3.2	2.4	2.8	3.1	1.0	1.5
s.d.	*2.7*	*2.9*	*2.6*	*2.6*	*2.8*	*0.9*	*1.4*
LIT nsc	2.9	2.9	2.2	2.6	2.8	0.9	1.3
s.d.	*2.6*	*2.7*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	7.2	7.1	9.9	6.2	6.7	3.6	4.8
s.d.	*5.0*	*5.4*	*3.3*	*5.2*	*5.6*	*1.5*	*2.3*
ADL(1,0) ml	6.6	6.3	8.8	5.6	5.9	3.4	4.6
s.d.	*6.6*	*6.7*	*5.2*	*6.5*	*6.7*	*3.5*	*4.2*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT ssr	**7.2**	**6.8**	**4.7**	**5.8**	**6.2**	**2.0**	**3.1**
s.d.	**6.4**	**6.0**	**4.7**	**5.3**	**5.6**	**2.0**	**3.0**
CL ssr	6.3	6.7	4.8	6.1	6.6	2.2	3.4
s.d.	*5.2*	*5.6*	*4.1*	*5.2*	*5.6*	*1.9*	*2.9*
CL ml	7.6	7.9	5.4	7.4	7.8	2.9	4.3
s.d.	*9.2*	*9.5*	*6.5*	*9.3*	*9.5*	*4.4*	*6.1*
FER	5.8	6.1	4.3	5.6	6.0	2.0	3.0
s.d.	*5.2*	*5.5*	*4.1*	*5.2*	*5.5*	*1.9*	*2.8*
LIT ml	3.2	3.2	2.5	2.8	3.1	1.0	1.5
s.d.	*2.7*	*2.9*	*2.6*	*2.6*	*2.8*	*0.9*	*1.4*
LIT nsc	2.9	2.9	2.3	2.6	2.8	0.9	1.4
s.d.	*2.6*	*2.7*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	7.2	7.1	9.9	6.2	6.7	3.6	4.8
s.d.	*4.9*	*5.4*	*3.3*	*5.2*	*5.6*	*1.5*	*2.3*
ADL(1,0) ml	6.6	6.4	8.8	5.6	5.9	3.4	4.6
s.d.	*6.6*	*6.7*	*5.2*	*6.5*	*6.8*	*3.5*	*4.2*

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	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT ml	**3.2**	**3.2**	**2.4**	**2.8**	**3.1**	**1.0**	**1.5**
s.d.	**2.7**	**2.9**	**2.6**	**2.6**	**2.8**	**0.9**	**1.4**
CL ssr	3.4	3.5	2.9	3.2	3.4	1.2	1.8
s.d.	*2.6*	*2.9*	*2.7*	*2.6*	*2.9*	*1.0*	*1.4*
CL ml	3.1	3.2	2.5	2.9	3.1	1.0	1.5
s.d.	*2.9*	*3.0*	*2.5*	*2.8*	*3.0*	*0.9*	*1.4*
FER	3.1	3.2	2.5	2.8	3.1	1.0	1.5
s.d.	*2.7*	*2.9*	*2.5*	*2.6*	*2.8*	*0.9*	*1.4*
LIT ssr	4.1	3.7	2.6	2.9	3.2	1.0	1.5
s.d.	*3.9*	*3.4*	*2.8*	*2.7*	*2.9*	*1.0*	*1.4*
LIT nsc	2.9	2.9	2.2	2.6	2.8	0.9	1.3
s.d.	*2.6*	*2.6*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	4.6	4.1	9.4	3.3	3.5	3.1	3.8
s.d.	*2.8*	*2.9*	*3.2*	*2.5*	*2.9*	*0.9*	*1.1*
ADL(1,0) ml	4.2	3.8	8.3	3.1	3.2	2.5	3.3
s.d.	*2.8*	*2.9*	*3.8*	*2.6*	*3.0*	*1.8*	*1.9*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT nsc	**2.9**	**2.9**	**2.2**	**2.6**	**2.8**	**0.9**	**1.3**
s.d.	**2.6**	**2.7**	**2.4**	**2.4**	**2.6**	**0.9**	**1.3**
CL ssr	3.1	3.2	2.7	2.9	3.1	1.1	1.6
s.d.	*2.4*	*2.6*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
CL ml	2.9	2.9	2.3	2.6	2.8	0.9	1.4
s.d.	*2.8*	*2.8*	*2.4*	*2.8*	*2.8*	*0.9*	*1.2*
FER	2.9	2.9	2.3	2.6	2.8	0.9	1.4
s.d.	*2.6*	*2.7*	*2.3*	*2.4*	*2.6*	*0.8*	*1.2*
LIT ssr	3.8	3.4	2.4	2.7	2.9	0.9	1.4
s.d.	*3.7*	*3.2*	*2.5*	*2.5*	*2.7*	*0.9*	*1.3*
LIT ml	2.9	2.9	2.2	2.6	2.8	0.9	1.4
s.d.	*2.6*	*2.6*	*2.3*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	4.3	3.8	9.4	3.1	3.2	3.1	3.7
s.d.	*2.7*	*2.7*	*3.2*	*2.4*	*2.7*	*0.8*	*1.1*
ADL(1,0) ml	4.0	3.5	8.3	2.8	3.0	2.5	3.2
s.d.	*2.6*	*2.6*	*3.8*	*2.3*	*2.7*	*1.7*	*1.9*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
ADL(1,0) ssr	**7.2**	**7.1**	**9.9**	**6.2**	**6.7**	**3.6**	**4.8**
s.d.	**5.0**	**5.4**	**3.3**	**5.2**	**5.6**	**1.5**	**2.3**
CL ssr	6.7	7.1	4.8	6.5	7.0	2.2	3.4
s.d.	*5.3*	*5.7*	*4.2*	*5.3*	*5.7*	*1.9*	*2.9*
CL ml	8.4	8.7	5.4	8.2	8.6	2.9	4.4
s.d.	*9.6*	*9.9*	*6.6*	*9.6*	*9.9*	*4.4*	*6.2*
FER	6.4	6.7	4.4	6.1	6.6	2.0	3.1
s.d.	*5.3*	*5.7*	*4.2*	*5.3*	*5.7*	*1.9*	*2.9*
LIT ssr	7.8	7.3	4.7	6.3	6.7	2.0	3.2
s.d.	*6.6*	*6.1*	*4.7*	*5.4*	*5.8*	*2.0*	*3.0*
LIT ml	3.4	3.5	2.4	3.1	3.3	1.0	1.5
s.d.	*2.9*	*3.0*	*2.5*	*2.7*	*3.0*	*0.9*	*1.4*
LIT nsc	3.2	3.2	2.2	2.8	3.0	0.9	1.3
s.d.	*2.8*	*2.8*	*2.3*	*2.5*	*2.8*	*0.9*	*1.2*
ADL(1,0) ml	7.1	6.9	8.7	6.1	6.5	3.4	4.6
s.d.	*7.0*	*7.1*	*5.3*	*6.8*	*7.0*	*3.5*	*4.3*

	I1	I2	I3	I1sa	I2sa	I3sa	I4
ADL(1,0) ml	**6.6**	**6.3**	**8.8**	**5.6**	**5.9**	**3.4**	**4.6**
s.d.	**6.6**	**6.7**	**5.2**	**6.5**	**6.7**	**3.5**	**4.2**
CL ssr	5.3	5.5	4.5	5.1	5.4	2.2	3.2
s.d.	*4.5*	*4.8*	*3.8*	*4.5*	*4.8*	*1.9*	*2.7*
CL ml	5.8	6.0	5.2	5.7	6.0	3.0	4.2
s.d.	*7.1*	*7.4*	*6.0*	*7.2*	*7.4*	*4.4*	*5.8*
FER	4.9	5.0	4.1	4.6	4.9	2.0	2.9
s.d.	*4.5*	*4.7*	*3.8*	*4.4*	*4.7*	*1.9*	*2.7*
LIT ssr	6.1	5.6	4.4	4.8	5.0	2.0	3.0
s.d.	*5.7*	*5.1*	*4.3*	*4.6*	*4.7*	*2.0*	*2.8*
LIT ml	3.2	3.2	2.6	2.8	3.1	1.0	1.5
s.d.	*2.7*	*2.9*	*2.6*	*2.5*	*2.8*	*1.0*	*1.4*
LIT nsc	2.9	2.9	2.4	2.6	2.8	0.9	1.4
s.d.	*2.5*	*2.6*	*2.4*	*2.4*	*2.6*	*0.9*	*1.3*
ADL(1,0) ssr	6.2	5.9	9.7	5.2	5.5	3.5	4.6
s.d.	*4.3*	*4.6*	*3.2*	*4.5*	*4.8*	*1.5*	*2.1*

Table 12: Out-of-sample period: Absolute annual percentage error for different DGPs for indicators.

	I1	I2	I3	I1sa	I2sa	I3sa	I4
CL ssr	**9.9**	**10.9**	**4.8**	**9.8**	**10.9**	**2.9**	**4.2**
s.d.	**12.3**	**14.0**	**5.0**	**12.3**	**14.0**	**3.1**	**4.6**
CL ml	9.1	10.2	4.2	9.1	10.2	2.5	3.7
s.d.	11.8	13.9	4.4	11.8	13.9	2.6	4.0
FER	10.3	11.3	5.0	10.2	11.3	3.0	4.5
s.d.	12.7	14.3	5.3	12.6	14.3	3.3	4.9
LIT ssr	14.7	16.0	7.5	14.7	16.0	4.5	6.8
s.d.	17.9	19.6	8.3	18.0	19.6	5.1	7.7
LIT ml	8.8	9.5	4.0	8.7	9.4	2.4	3.5
s.d.	11.6	12.8	4.3	11.6	12.8	2.7	3.8
LIT nsc	8.5	9.0	3.9	8.4	9.0	2.3	3.4
s.d.	11.5	12.7	4.1	11.5	12.7	2.5	3.7
ADL(1,0) ssr	10.5	11.6	5.8	10.4	11.5	4.0	5.3
s.d.	12.3	14.0	5.4	12.3	14.0	3.7	5.0
ADL(1,0) ml	9.5	10.3	5.1	9.5	10.3	3.3	4.5
s.d.	11.9	13.3	4.9	11.9	13.3	3.2	4.4

	I1	I2	I3	I1sa	I2sa	I3sa	I4
CL ml	**8.7**	**9.8**	**4.0**	**8.6**	**9.8**	**2.4**	**3.5**
s.d.	**11.4**	**13.6**	**4.3**	**11.3**	**13.6**	**2.6**	**3.9**
CL ssr	9.7	10.6	4.7	9.6	10.6	2.9	4.2
s.d.	12.1	13.7	5.0	12.1	13.7	3.1	4.6
FER	9.4	10.5	4.8	9.3	10.4	2.9	4.3
s.d.	11.9	13.6	5.1	11.9	13.6	3.2	4.7
LIT ssr	13.2	14.5	6.9	13.2	14.5	4.2	6.3
s.d.	16.7	18.1	7.9	16.8	18.2	5.0	7.4
LIT ml	7.9	8.7	3.7	7.8	8.7	2.2	3.3
s.d.	10.7	12.3	4.2	10.7	12.3	2.5	3.7
LIT nsc	7.5	8.3	3.5	7.4	8.3	2.1	3.1
s.d.	10.6	12.2	4.0	10.5	12.2	2.4	3.6
ADL(1,0) ssr	9.8	11.0	5.7	9.7	10.9	4.0	5.3
s.d.	11.8	13.5	5.3	11.7	13.5	3.7	5.0
ADL(1,0) ml	9.0	10.0	5.1	9.0	10.0	3.3	4.5
s.d.	11.3	13.1	4.8	11.3	13.1	3.2	4.4

	I1	I2	I3	I1sa	I2sa	I3sa	I4
FER	**9.6**	**10.8**	**4.8**	**9.6**	**10.8**	**2.9**	**4.3**
s.d.	**12.1**	**14.0**	**5.2**	**12.1**	**14.0**	**3.2**	**4.8**
CL ssr	9.9	10.9	4.8	9.8	10.9	2.9	4.2
s.d.	12.3	14.0	5.0	12.3	14.0	3.1	4.6
CL ml	8.7	9.8	4.0	8.6	9.8	2.4	3.5
s.d.	11.4	13.6	4.3	11.3	13.6	2.6	3.9
LIT ssr	13.6	15.1	6.9	13.6	15.1	4.2	6.3
s.d.	17.2	19.0	8.0	17.2	19.0	5.0	7.5
LIT ml	7.9	8.8	3.7	7.8	8.7	2.2	3.3
s.d.	10.7	12.3	4.2	10.7	12.3	2.5	3.7
LIT nsc	7.5	8.3	3.5	7.4	8.3	2.1	3.1
s.d.	10.6	12.2	4.0	10.5	12.1	2.4	3.6
ADL(1,0) ssr	10.1	11.2	5.7	10.0	11.2	4.0	5.3
s.d.	12.0	13.8	5.3	11.9	13.8	3.7	5.0
ADL(1,0) ml	9.1	10.1	5.1	9.0	10.0	3.3	4.5
s.d.	11.4	13.1	4.8	11.3	13.1	3.2	4.4

	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT ssr	**13.6**	**15.1**	**6.9**	**13.6**	**15.1**	**4.2**	**6.3**
s.d.	**17.2**	**19.0**	**8.0**	**17.2**	**19.0**	**5.0**	**7.5**
CL ssr	9.7	10.8	4.8	9.6	10.8	2.9	4.2
s.d.	12.0	13.8	5.0	12.0	13.8	3.1	4.6
CL ml	8.6	9.7	4.0	8.5	9.7	2.4	3.6
s.d.	11.3	13.6	4.3	11.2	13.6	2.6	3.9
FER	9.4	10.7	4.8	9.3	10.7	2.9	4.3
s.d.	11.8	13.8	5.2	11.8	13.8	3.2	4.8
LIT ml	7.8	8.7	3.7	7.7	8.7	2.2	3.3
s.d.	10.5	12.2	4.2	10.5	12.2	2.6	3.7
LIT nsc	7.4	8.2	3.6	7.3	8.3	2.1	3.1
s.d.	10.3	12.1	4.0	10.4	12.2	2.4	3.6
ADL(1,0) ssr	9.8	11.1	5.7	9.8	11.1	4.0	5.3
s.d.	11.7	13.6	5.3	11.7	13.6	3.7	5.0
ADL(1,0) ml	9.0	10.0	5.1	8.9	10.0	3.3	4.5
s.d.	11.3	13.1	4.8	11.3	13.1	3.2	4.4

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continued from previous page

	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT ml	7.9	8.8	3.7	7.8	8.7	2.2	3.3
s.d.	10.7	12.3	4.2	10.7	12.3	2.5	3.7
CL ssr	8.9	9.6	3.9	8.8	9.6	2.3	3.4
s.d.	11.8	13.1	4.2	11.7	13.1	2.6	3.7
CL ml	8.4	9.5	3.5	8.3	9.5	2.1	3.0
s.d.	11.8	13.8	3.8	11.8	13.8	2.3	3.3
FER	8.1	9.0	3.8	8.0	9.0	2.3	3.3
s.d.	10.9	12.6	4.1	10.9	12.7	2.5	3.6
LIT ssr	10.1	11.0	4.9	10.0	11.0	2.9	4.3
s.d.	13.5	14.9	5.8	13.6	14.9	3.5	5.2
LIT nsc	7.5	8.3	3.5	7.4	8.3	2.1	3.1
s.d.	10.6	12.2	4.0	10.6	12.2	2.4	3.6
ADL(1,0) ssr	9.1	10.1	5.4	9.0	10.1	4.0	5.0
s.d.	11.3	12.9	4.8	11.2	12.9	3.6	4.5
ADL(1,0) ml	8.8	10.0	5.2	8.8	9.9	3.5	4.7
s.d.	11.5	13.2	4.6	11.5	13.2	3.2	4.3

	I1	I2	I3	I1sa	I2sa	I3sa	I4
LIT nsc	7.5	8.3	3.5	7.4	8.3	2.1	3.1
s.d.	10.6	12.2	4.0	10.5	12.1	2.4	3.6
CL ssr	8.6	9.2	3.7	8.5	9.2	2.2	3.2
s.d.	11.8	13.1	4.0	11.8	13.1	2.5	3.6
CL ml	8.1	9.1	3.3	8.0	9.1	2.0	2.9
s.d.	11.6	13.6	3.6	11.6	13.6	2.2	3.2
FER	7.8	8.7	3.6	7.7	8.6	2.2	3.1
s.d.	10.8	12.5	3.9	10.8	12.5	2.4	3.5
LIT ssr	9.5	10.4	4.6	9.4	10.4	2.7	4.0
s.d.	12.9	14.5	5.4	13.0	14.6	3.3	5.0
LIT ml	7.5	8.3	3.6	7.5	8.3	2.1	3.1
s.d.	10.6	12.1	4.0	10.6	12.1	2.5	3.6
ADL(1,0) ssr	8.7	9.7	5.3	8.7	9.7	4.0	4.9
s.d.	11.1	12.8	4.7	11.1	12.8	3.6	4.4
ADL(1,0) ml	8.6	9.6	5.1	8.6	9.6	3.5	4.6
s.d.	11.4	12.9	4.6	11.3	12.9	3.2	4.2

	I1	I2	I3	I1sa	I2sa	I3sa	I4
ADL(1,0) ssr	10.1	11.2	5.7	10.0	11.2	4.0	5.3
s.d.	12.0	13.8	5.3	11.9	13.8	3.7	5.0
CL ssr	10.0	11.2	4.8	10.0	11.2	2.9	4.2
s.d.	12.3	14.2	5.0	12.3	14.2	3.1	4.6
CL ml	8.8	10.1	4.0	8.8	10.0	2.4	3.5
s.d.	11.4	13.9	4.3	11.4	13.9	2.6	3.9
FER	10.0	11.2	4.8	9.9	11.2	2.9	4.3
s.d.	12.3	14.4	5.1	12.2	14.4	3.2	4.8
LIT ssr	14.3	15.8	6.9	14.3	15.8	4.2	6.3
s.d.	17.5	19.3	8.0	17.5	19.4	5.0	7.5
LIT ml	8.2	9.2	3.7	8.1	9.2	2.2	3.2
s.d.	11.0	13.0	4.1	10.9	13.0	2.5	3.6
LIT nsc	7.8	8.7	3.4	7.7	8.7	2.1	3.0
s.d.	10.8	12.9	3.9	10.8	12.9	2.4	3.5
ADL(1,0) ml	9.2	10.3	5.0	9.2	10.3	3.3	4.5
s.d.	11.3	13.3	4.8	11.3	13.3	3.1	4.3

	I1	I2	I3	I1sa	I2sa	I3sa	I4
ADL(1,0) ml	9.1	10.1	5.1	9.0	10.0	3.3	4.5
s.d.	11.4	13.1	4.8	11.3	13.1	3.2	4.4
CL ssr	9.4	10.3	4.6	9.4	10.2	2.7	4.0
s.d.	11.8	13.3	4.8	11.9	13.3	3.0	4.3
CL ml	8.6	9.7	4.0	8.6	9.7	2.3	3.4
s.d.	11.2	13.3	4.2	11.2	13.3	2.5	3.8
FER	9.0	10.0	4.6	9.0	10.0	2.8	4.1
s.d.	11.5	13.2	4.9	11.5	13.2	3.1	4.5
LIT ssr	12.4	13.5	6.6	12.4	13.6	4.1	6.1
s.d.	16.2	17.2	7.4	16.2	17.3	4.8	7.0
LIT ml	7.9	8.7	3.9	7.8	8.7	2.2	3.3
s.d.	10.5	12.2	4.3	10.4	12.2	2.5	3.7
LIT nsc	7.5	8.3	3.7	7.4	8.3	2.1	3.2
s.d.	10.4	12.0	4.1	10.4	12.0	2.4	3.6
ADL(1,0) ssr	9.6	10.7	5.6	9.6	10.7	3.8	5.1
s.d.	11.5	13.2	5.2	11.5	13.2	3.6	4.8

Table 13: In-sample period: RMSPEL for different DGPs for disturbances.

	C1	C5	C9	F	L1	L5	L9
CL ssr	**10.4**	**8.5**	**4.8**	**3.3**	**3.0**	**2.1**	**0.8**
s.d.	***6.0***	***5.0***	***3.1***	***2.5***	***2.3***	***1.7***	***0.8***
CL ml	16.2	13.7	4.9	3.4	3.1	2.1	0.8
s.d.	*10.9*	*10.6*	*3.5*	*2.7*	*2.4*	*1.7*	*0.8*
FER	10.4	8.5	4.8	3.3	3.1	2.1	0.8
s.d.	*6.0*	*5.0*	*3.1*	*2.5*	*2.3*	*1.7*	*0.8*
LIT ssr	10.9	9.1	5.2	3.7	3.3	2.3	0.9
LIT ml	10.1	7.7	4.6	3.2	2.9	2.0	0.8
s.d.	*6.0*	*4.6*	*3.0*	*2.3*	*2.2*	*1.7*	*0.8*
LIT nsc	11.0	8.2	4.4	3.1	2.8	2.0	0.8
s.d.	*6.8*	*4.7*	*2.9*	*2.2*	*2.1*	*1.6*	*0.8*
ADL(1,0) ssr	11.0	9.3	6.2	5.0	4.8	4.2	2.8
s.d.	*5.7*	*4.6*	*3.1*	*2.9*	*2.9*	*3.0*	*2.9*
ADL(1,0) ml	12.1	10.5	5.9	4.6	4.4	3.6	2.3
s.d.	*9.2*	*8.7*	*3.4*	*3.1*	*2.9*	*2.8*	*2.9*

	C1	C5	C9	F	L1	L5	L9
CL ml	**16.2**	**13.8**	**4.9**	**3.4**	**3.1**	**2.0**	**0.7**
s.d.	***10.9***	***10.6***	***3.6***	***2.7***	***2.3***	***1.7***	***0.8***
CL ssr	10.1	8.0	4.8	3.3	3.0	2.1	0.8
s.d.	*5.8*	*4.8*	*3.1*	*2.4*	*2.3*	*1.7*	*0.8*
FER	10.1	8.1	4.8	3.3	3.0	2.0	0.7
s.d.	*5.8*	*4.8*	*3.1*	*2.4*	*2.2*	*1.7*	*0.8*
LIT ssr	10.7	8.6	5.2	3.7	3.4	2.3	0.7
LIT ml	10.4	7.9	4.6	3.1	2.9	2.0	0.7
s.d.	*5.8*	*4.6*	*3.0*	*2.3*	*2.1*	*1.6*	*0.8*
LIT nsc	11.8	8.7	4.4	3.1	2.9	2.0	0.6
s.d.	*5.8*	*4.8*	*2.9*	*2.3*	*2.1*	*1.6*	*0.7*
ADL(1,0) ssr	10.8	8.9	6.2	5.0	4.8	4.2	3.5
s.d.	*5.5*	*4.5*	*3.1*	*2.9*	*2.9*	*3.0*	*3.3*
ADL(1,0) ml	12.1	10.3	5.9	4.6	4.4	3.6	2.8
s.d.	*9.2*	*8.6*	*3.4*	*3.0*	*2.9*	*2.8*	*3.2*

	C1	C5	C9	F	L1	L5	L9
FER	**10.4**	**8.6**	**4.8**	**3.3**	**3.0**	**2.0**	**0.7**
s.d.	***6.0***	***5.0***	***3.1***	***2.5***	***2.2***	***1.7***	***0.8***
CL ssr	10.4	8.5	4.8	3.3	3.0	2.1	0.8
s.d.	*6.0*	*5.0*	*3.1*	*2.5*	*2.3*	*1.7*	*0.8*
CL ml	16.2	13.8	4.9	3.4	3.1	2.0	0.7
s.d.	*10.9*	*10.6*	*3.6*	*2.7*	*2.3*	*1.7*	*0.8*
LIT ssr	11.0	9.1	5.2	3.7	3.4	2.3	0.7
s.d.	*6.5*	*5.6*	*3.7*	*3.0*	*2.7*	*2.2*	*0.9*
LIT ml	10.9	8.0	4.6	3.1	2.9	2.0	0.7
s.d.	*6.1*	*4.7*	*3.0*	*2.3*	*2.1*	*1.6*	*0.8*
LIT nsc	12.3	8.8	4.4	3.1	2.9	2.0	0.6
s.d.	*6.2*	*4.9*	*2.9*	*2.3*	*2.1*	*1.6*	*0.7*
ADL(1,0) ssr	11.0	9.3	6.2	5.0	4.8	4.2	3.5
s.d.	*5.7*	*4.6*	*3.1*	*2.9*	*2.9*	*3.0*	*3.3*
ADL(1,0) ml	12.2	10.5	5.9	4.6	4.4	3.6	2.8
s.d.	*9.2*	*8.6*	*3.4*	*3.0*	*2.9*	*2.8*	*3.2*

	C1	C5	C9	F	L1	L5	L9
LIT ssr	**11.0**	**9.1**	**5.2**	**3.7**	**3.4**	**2.3**	**0.7**
s.d.	***6.5***	***5.6***	***3.7***	***3.0***	***2.7***	***2.2***	***0.9***
CL ssr	10.3	8.4	4.7	3.3	3.0	2.0	0.8
s.d.	*6.0*	*4.9*	*3.1*	*2.4*	*2.3*	*1.7*	*0.8*
CL ml	16.2	13.6	4.8	3.4	3.0	2.0	0.7
s.d.	*10.9*	*10.5*	*3.5*	*2.6*	*2.3*	*1.7*	*0.8*
FER	10.4	8.5	4.7	3.3	3.0	2.0	0.7
s.d.	*6.0*	*5.0*	*3.1*	*2.4*	*2.2*	*1.7*	*0.8*
LIT ml	10.8	8.0	4.5	3.1	2.9	2.0	0.6
s.d.	*6.1*	*4.7*	*3.0*	*2.3*	*2.1*	*1.6*	*0.7*
LIT nsc	12.2	8.8	4.4	3.1	2.8	1.9	0.6
s.d.	*6.2*	*4.9*	*2.9*	*2.2*	*2.1*	*1.6*	*0.7*
ADL(1,0) ssr	11.0	9.3	6.2	5.0	4.8	4.2	3.5
s.d.	*5.7*	*4.6*	*3.1*	*2.9*	*2.9*	*3.0*	*3.3*
ADL(1,0) ml	12.1	10.4	5.8	4.6	4.3	3.6	2.8
s.d.	*9.2*	*8.5*	*3.4*	*3.0*	*2.9*	*2.8*	*3.2*

continued on next page

continued from previous page

	C1	C5	C9	F	L1	L5	L9
LIT ml	**10.9**	**8.0**	**4.6**	**3.1**	**2.9**	**2.0**	**0.7**
s.d.	***6.1***	***4.7***	***3.0***	***2.3***	***2.1***	***1.6***	***0.8***
CL ssr	10.1	7.7	4.5	3.1	2.9	2.0	0.8
s.d.	*6.0*	*4.5*	*3.0*	*2.3*	*2.1*	*1.7*	*0.8*
CL ml	13.3	8.2	4.5	3.1	2.9	2.0	0.7
s.d.	*10.0*	*5.7*	*3.0*	*2.3*	*2.1*	*1.6*	*0.8*
FER	10.9	8.0	4.6	3.1	2.9	2.0	0.7
s.d.	*6.2*	*4.6*	*3.0*	*2.3*	*2.1*	*1.6*	*0.8*
LIT ssr	11.6	8.5	5.0	3.4	3.2	2.3	0.7
s.d.	*6.9*	*5.2*	*3.6*	*2.7*	*2.6*	*2.1*	*0.9*
LIT nsc	11.9	8.6	4.4	3.1	2.9	2.0	0.6
s.d.	*6.5*	*4.9*	*2.9*	*2.3*	*2.1*	*1.6*	*0.7*
ADL(1,0) ssr	11.5	8.9	6.1	4.9	4.8	4.2	3.5
s.d.	*5.8*	*4.4*	*3.1*	*2.9*	*2.8*	*3.0*	*3.3*
ADL(1,0) ml	12.9	8.6	5.8	4.5	4.3	3.6	2.8
s.d.	*8.9*	*5.0*	*3.3*	*2.9*	*2.8*	*2.8*	*3.2*

	C1	C5	C9	F	L1	L5	L9
LIT nsc	**12.3**	**8.8**	**4.4**	**3.1**	**2.9**	**2.0**	**0.6**
s.d.	***6.2***	***4.9***	***2.9***	***2.3***	***2.1***	***1.6***	***0.7***
CL ssr	10.9	8.1	4.4	3.1	2.8	1.9	0.8
s.d.	*6.8*	*4.7*	*2.8*	*2.2*	*2.1*	*1.6*	*0.8*
CL ml	16.5	9.9	4.4	3.0	2.8	1.9	0.7
s.d.	*10.4*	*7.5*	*3.0*	*2.2*	*2.1*	*1.6*	*0.8*
FER	12.3	8.7	4.4	3.0	2.8	1.9	0.7
s.d.	*6.3*	*4.9*	*2.9*	*2.2*	*2.1*	*1.6*	*0.8*
LIT ssr	13.9	9.6	4.8	3.3	3.1	2.2	0.7
s.d.	*7.7*	*5.8*	*3.4*	*2.7*	*2.5*	*2.1*	*0.9*
LIT ml	12.0	8.6	4.4	3.1	2.9	1.9	0.7
s.d.	*6.5*	*4.9*	*2.9*	*2.2*	*2.1*	*1.6*	*0.8*
ADL(1,0) ssr	12.6	9.5	6.0	4.9	4.7	4.2	3.5
s.d.	*5.9*	*4.4*	*3.0*	*2.9*	*2.9*	*3.0*	*3.3*
ADL(1,0) ml	13.0	9.6	5.6	4.5	4.3	3.6	2.8
s.d.	*7.8*	*5.6*	*3.1*	*2.8*	*2.8*	*2.8*	*3.2*

	C1	C5	C9	F	L1	L5	L9
ADL(1,0) ssr	**11.0**	**9.3**	**6.2**	**5.0**	**4.8**	**4.2**	**3.5**
s.d.	***5.7***	***4.6***	***3.1***	***2.9***	***2.9***	***3.0***	***3.3***
CL ssr	10.4	8.5	4.8	3.3	3.1	2.0	0.8
s.d.	*6.0*	*5.0*	*3.1*	*2.5*	*2.3*	*1.8*	*0.8*
CL ml	16.3	13.8	4.9	3.4	3.1	2.0	0.7
s.d.	*10.9*	*10.7*	*3.6*	*2.7*	*2.4*	*1.7*	*0.8*
FER	10.4	8.6	4.8	3.3	3.0	2.0	0.7
s.d.	*6.0*	*5.0*	*3.1*	*2.5*	*2.3*	*1.7*	*0.8*
LIT ssr	11.0	9.1	5.2	3.7	3.4	2.3	0.7
s.d.	*6.5*	*5.6*	*3.8*	*3.1*	*2.7*	*2.3*	*0.9*
LIT ml	10.9	8.0	4.6	3.1	2.9	1.9	0.6
s.d.	*6.2*	*4.7*	*3.0*	*2.3*	*2.2*	*1.7*	*0.7*
LIT nsc	12.3	8.8	4.4	3.0	2.8	1.9	0.6
s.d.	*6.2*	*4.9*	*2.9*	*2.3*	*2.1*	*1.6*	*0.7*
ADL(1,0) ml	12.2	10.5	5.9	4.6	4.4	3.7	3.0
s.d.	*9.2*	*8.6*	*3.4*	*3.0*	*2.9*	*2.8*	*3.4*

	C1	C5	C9	F	L1	L5	L9
ADL(1,0) ml	**12.2**	**10.5**	**5.9**	**4.6**	**4.4**	**3.6**	**2.8**
s.d.	***9.2***	***8.6***	***3.4***	***3.0***	***2.9***	***2.8***	***3.2***
CL ssr	8.8	7.3	4.8	3.4	3.1	2.1	0.8
s.d.	*5.5*	*4.8*	*3.1*	*2.4*	*2.2*	*1.7*	*0.8*
CL ml	13.6	12.1	4.9	3.4	3.1	2.1	0.8
s.d.	*9.4*	*9.6*	*3.3*	*2.5*	*2.3*	*1.6*	*0.8*
FER	8.9	7.3	4.9	3.4	3.1	2.1	0.8
s.d.	*5.6*	*4.8*	*3.2*	*2.4*	*2.2*	*1.7*	*0.8*
LIT ssr	9.3	7.8	5.3	3.7	3.4	2.4	0.8
s.d.	*6.0*	*5.4*	*3.7*	*3.0*	*2.6*	*2.2*	*0.9*
LIT ml	10.7	7.8	4.7	3.2	3.0	2.0	0.7
s.d.	*6.3*	*4.7*	*3.0*	*2.3*	*2.2*	*1.6*	*0.8*
LIT nsc	11.5	8.7	4.6	3.2	3.0	2.0	0.7
s.d.	*6.9*	*5.0*	*2.9*	*2.3*	*2.1*	*1.6*	*0.8*
ADL(1,0) ssr	9.6	8.3	6.2	5.0	4.7	4.0	3.2
s.d.	*5.3*	*4.5*	*3.1*	*2.9*	*2.8*	*2.8*	*3.1*

Table 14: Out-of-sample period: Absolute annual percentage error for different DGPs for disturbances.

	C1	C5	C9	F	L1	L5	L9
CL ssr	**7.5**	**10.2**	**8.8**	**6.7**	**6.5**	**6.7**	**5.1**
s.d.	***8.8***	***12.9***	***12.4***	***9.7***	***9.1***	***11.5***	***8.4***
CL ml	5.3	7.4	8.6	7.2	6.6	7.1	5.4
s.d.	*6.0*	*9.6*	*12.3*	*11.0*	*9.6*	*13.3*	*9.1*
FER	8.4	11.0	8.9	6.8	6.6	6.7	5.1
s.d.	*9.8*	*13.6*	*12.5*	*9.7*	*9.2*	*11.5*	*8.3*
LIT ssr	14.0	17.1	13.2	9.4	8.8	8.2	4.3
s.d.	*16.3*	*20.1*	*17.0*	*13.0*	*12.1*	*12.9*	*6.7*
LIT ml	8.5	11.2	8.7	6.7	6.1	6.8	4.1
s.d.	*9.3*	*17.7*	*10.9*	*9.4*	*8.7*	*11.4*	*6.3*
LIT nsc	4.4	14.8	8.4	6.4	5.9	6.8	4.2
s.d.	*4.4*	*20.9*	*10.9*	*8.8*	*8.7*	*11.7*	*6.4*
ADL(1,0) ssr	7.6	10.2	9.5	7.4	7.6	7.9	6.7
s.d.	*8.8*	*12.6*	*12.5*	*9.3*	*9.3*	*11.4*	*9.0*
ADL(1,0) ml	4.7	7.0	8.8	7.9	7.4	8.4	6.9
s.d.	*5.3*	*9.7*	*11.5*	*10.6*	*9.1*	*12.5*	*9.7*

	C1	C5	C9	F	L1	L5	L9
CL ml	**5.3**	**7.5**	**8.5**	**7.2**	**6.7**	**7.2**	**4.3**
s.d.	***6.0***	***9.7***	***12.1***	***10.7***	***9.8***	***13.0***	***7.5***
CL ssr	7.2	9.5	8.8	6.7	6.5	6.7	5.1
s.d.	*8.3*	*12.1*	*12.4*	*9.7*	*9.1*	*11.5*	*8.4*
FER	8.1	10.2	8.9	6.7	6.7	6.8	4.2
s.d.	*9.2*	*12.7*	*12.3*	*9.5*	*9.3*	*11.2*	*7.0*
LIT ssr	13.4	15.9	13.2	9.3	9.0	8.2	3.3
s.d.	*15.3*	*18.7*	*16.8*	*12.8*	*12.2*	*12.5*	*5.7*
LIT ml	7.9	11.7	8.7	6.7	6.2	6.8	3.2
s.d.	*8.3*	*18.0*	*10.7*	*9.2*	*8.9*	*11.1*	*5.5*
LIT nsc	6.2	14.3	8.3	6.4	6.0	6.8	3.2
s.d.	*5.0*	*20.9*	*10.7*	*8.5*	*8.9*	*11.3*	*5.5*
ADL(1,0) ssr	7.2	9.5	9.4	7.4	7.7	8.0	5.6
s.d.	*8.3*	*11.8*	*12.3*	*9.1*	*9.4*	*11.3*	*7.2*
ADL(1,0) ml	4.6	6.8	8.8	7.9	7.5	8.4	5.9
s.d.	*5.2*	*9.5*	*11.3*	*10.4*	*9.5*	*12.4*	*8.2*

	C1	C5	C9	F	L1	L5	L9
FER	**8.5**	**11.0**	**8.9**	**6.7**	**6.7**	**6.8**	**4.2**
s.d.	***9.8***	***13.6***	***12.3***	***9.5***	***9.3***	***11.2***	***7.0***
CL ssr	7.5	10.2	8.8	6.7	6.5	6.7	5.1
s.d.	*8.8*	*12.9*	*12.4*	*9.7*	*9.1*	*11.5*	*8.4*
CL ml	5.3	7.5	8.5	7.2	6.7	7.2	4.3
s.d.	*6.0*	*9.7*	*12.1*	*10.7*	*9.8*	*13.0*	*7.5*
LIT ssr	14.1	17.1	13.3	9.3	9.0	8.2	3.3
s.d.	*16.3*	*20.1*	*16.8*	*12.8*	*12.2*	*12.5*	*5.7*
LIT ml	8.2	11.7	8.7	6.7	6.2	6.8	3.2
s.d.	*8.5*	*17.9*	*10.7*	*9.2*	*8.9*	*11.1*	*5.5*
LIT nsc	6.3	14.4	8.3	6.4	6.0	6.8	3.2
s.d.	*4.9*	*20.8*	*10.7*	*8.5*	*8.9*	*11.3*	*5.5*
ADL(1,0) ssr	7.6	10.2	9.5	7.4	7.7	8.0	5.6
s.d.	*8.7*	*12.6*	*12.3*	*9.2*	*9.4*	*11.3*	*7.2*
ADL(1,0) ml	4.7	7.1	8.8	7.9	7.5	8.4	5.9
s.d.	*5.3*	*9.8*	*11.3*	*10.4*	*9.5*	*12.4*	*8.2*

	C1	C5	C9	F	L1	L5	L9
LIT ssr	**14.1**	**17.1**	**13.3**	**9.3**	**9.0**	**8.2**	**3.3**
s.d.	***16.3***	***20.1***	***16.8***	***12.8***	***12.2***	***12.5***	***5.7***
CL ssr	7.5	9.9	8.6	6.7	6.4	6.7	5.0
s.d.	*8.8*	*12.6*	*12.1*	*9.5*	*9.0*	*11.5*	*8.1*
CL ml	5.3	7.4	8.4	7.1	6.5	7.2	4.1
s.d.	*6.0*	*9.6*	*11.9*	*10.7*	*9.7*	*13.0*	*7.1*
FER	8.4	10.6	8.7	6.7	6.6	6.8	4.0
s.d.	*9.8*	*13.1*	*12.0*	*9.3*	*9.2*	*11.2*	*6.8*
LIT ml	8.2	11.7	8.4	6.6	6.2	6.7	3.1
s.d.	*8.5*	*18.0*	*10.2*	*9.0*	*8.9*	*11.0*	*5.3*
LIT nsc	6.3	14.6	8.1	6.3	5.9	6.7	3.2
s.d.	*4.9*	*21.1*	*10.3*	*8.4*	*8.8*	*11.2*	*5.4*
ADL(1,0) ssr	7.5	9.9	9.2	7.3	7.6	8.0	5.5
s.d.	*8.7*	*12.2*	*12.0*	*9.0*	*9.3*	*11.2*	*7.1*
ADL(1,0) ml	4.7	7.0	8.7	7.9	7.4	8.4	5.8
s.d.	*5.3*	*9.8*	*11.2*	*10.4*	*9.4*	*12.4*	*7.9*

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	C1	C5	C9	F	L1	L5	L9
LIT ml	**8.2**	**11.7**	**8.7**	**6.7**	**6.2**	**6.8**	**3.2**
s.d.	***8.5***	***17.9***	***10.7***	***9.2***	***8.9***	***11.1***	***5.5***
CL ssr	7.9	10.3	8.5	6.5	6.1	6.7	5.1
s.d.	*8.9*	*16.4*	*10.9*	*9.2*	*8.9*	*11.6*	*8.4*
CL ml	6.0	7.8	8.2	6.7	6.2	7.2	4.3
s.d.	*6.5*	*12.1*	*11.1*	*9.8*	*9.6*	*13.0*	*7.5*
FER	8.2	11.3	8.5	6.5	6.2	6.8	4.2
s.d.	*8.3*	*16.8*	*10.7*	*9.0*	*9.1*	*11.3*	*7.0*
LIT ssr	14.2	17.5	11.9	8.9	8.4	8.0	3.3
s.d.	*15.1*	*24.9*	*13.5*	*12.2*	*11.7*	*12.2*	*5.7*
LIT nsc	5.7	15.6	8.4	6.4	6.0	6.8	3.2
s.d.	*4.7*	*21.3*	*10.7*	*8.6*	*8.9*	*11.3*	*5.5*
ADL(1,0) ssr	7.9	10.8	9.0	7.1	7.3	8.0	5.6
s.d.	*8.5*	*16.0*	*10.6*	*8.3*	*9.1*	*11.3*	*7.2*
ADL(1,0) ml	6.3	8.2	8.8	7.5	7.2	8.5	5.9
s.d.	*7.4*	*11.9*	*11.1*	*9.9*	*9.2*	*12.4*	*8.2*

	C1	C5	C9	F	L1	L5	L9
LIT nsc	**6.3**	**14.4**	**8.3**	**6.4**	**6.0**	**6.8**	**3.2**
s.d.	***4.9***	***20.8***	***10.7***	***8.5***	***8.9***	***11.3***	***5.5***
CL ssr	3.9	13.8	8.2	6.2	5.9	6.7	5.1
s.d.	*4.2*	*19.9*	*10.9*	*8.7*	*8.8*	*11.8*	*8.4*
CL ml	5.0	10.4	7.7	6.3	5.9	7.2	4.3
s.d.	*4.9*	*14.3*	*10.6*	*8.9*	*9.5*	*13.2*	*7.5*
FER	6.6	14.0	8.1	6.2	6.0	6.7	4.2
s.d.	*5.5*	*19.9*	*10.6*	*8.4*	*9.1*	*11.4*	*7.0*
LIT ssr	15.7	23.6	11.1	8.7	8.0	8.0	3.3
s.d.	*17.3*	*30.2*	*13.0*	*11.5*	*11.4*	*12.3*	*5.7*
LIT ml	5.7	16.1	8.5	6.4	6.0	6.8	3.2
s.d.	*4.7*	*22.0*	*10.8*	*8.6*	*8.9*	*11.2*	*5.5*
ADL(1,0) ssr	5.8	14.0	8.6	6.8	6.9	8.0	5.6
s.d.	*4.7*	*19.3*	*10.4*	*7.7*	*8.9*	*11.5*	*7.2*
ADL(1,0) ml	4.6	10.5	8.4	7.3	6.9	8.4	5.9
s.d.	*4.1*	*14.7*	*10.6*	*9.1*	*9.0*	*12.5*	*8.2*

	C1	C5	C9	F	L1	L5	L9
ADL(1,0) ssr	**7.6**	**10.2**	**9.5**	**7.4**	**7.7**	**8.0**	**5.6**
s.d.	***8.7***	***12.6***	***12.3***	***9.2***	***9.4***	***11.3***	***7.2***
CL ssr	7.5	10.1	8.8	6.5	6.5	6.7	5.0
s.d.	*8.8*	*12.6*	*12.4*	*9.3*	*9.2*	*11.9*	*8.8*
CL ml	5.3	7.5	8.5	6.9	6.6	7.2	3.9
s.d.	*6.0*	*9.7*	*12.0*	*10.1*	*10.0*	*13.2*	*7.2*
FER	8.5	10.9	8.8	6.5	6.7	6.8	3.8
s.d.	*9.8*	*13.3*	*12.4*	*9.1*	*9.4*	*11.6*	*6.9*
LIT ssr	14.1	16.8	13.2	9.1	8.9	8.1	3.1
s.d.	*16.3*	*19.3*	*16.8*	*12.9*	*12.2*	*12.8*	*5.5*
LIT ml	8.0	11.7	8.6	6.3	6.2	6.7	3.0
s.d.	*8.3*	*17.9*	*10.7*	*8.6*	*9.0*	*11.4*	*5.2*
LIT nsc	6.3	14.5	8.2	6.0	5.8	6.7	3.0
s.d.	*4.9*	*20.9*	*10.6*	*7.8*	*8.9*	*11.7*	*5.3*
ADL(1,0) ml	4.7	7.0	8.7	7.6	7.5	8.5	5.8
s.d.	*5.3*	*9.7*	*11.3*	*9.5*	*9.5*	*12.7*	*7.9*

	C1	C5	C9	F	L1	L5	L9
ADL(1,0) ml	**4.7**	**7.1**	**8.8**	**7.9**	**7.5**	**8.4**	**5.9**
s.d.	***5.3***	***9.8***	***11.3***	***10.4***	***9.5***	***12.4***	***8.2***
CL ssr	6.1	8.9	8.7	6.9	6.5	6.9	5.3
s.d.	*7.0*	*12.4*	*11.9*	*9.4*	*8.8*	*11.5*	*8.5*
CL ml	4.5	6.8	8.5	7.3	6.7	7.5	4.6
s.d.	*5.2*	*9.5*	*11.4*	*10.3*	*9.5*	*13.1*	*7.8*
FER	6.9	9.5	8.9	6.9	6.7	7.0	4.4
s.d.	*7.8*	*13.0*	*11.9*	*9.2*	*9.1*	*11.2*	*7.3*
LIT ssr	11.4	14.6	13.4	9.5	9.1	8.4	3.6
s.d.	*12.9*	*18.7*	*17.1*	*12.6*	*12.0*	*12.6*	*6.0*
LIT ml	8.2	12.1	8.9	6.9	6.3	7.0	3.5
s.d.	*8.8*	*18.8*	*10.9*	*9.3*	*8.7*	*11.2*	*5.7*
LIT nsc	5.0	15.0	8.6	6.6	6.1	7.0	3.4
s.d.	*4.1*	*22.0*	*11.0*	*8.9*	*8.5*	*11.3*	*5.8*
ADL(1,0) ssr	6.2	8.9	9.4	7.4	7.7	8.2	5.8
s.d.	*7.0*	*12.1*	*11.9*	*8.9*	*9.2*	*11.2*	*7.6*

Table 15: Ranking (adjusted for non admissible solutions) by different DGPs for indicators.

	In-sample period							
	I1	I2	I3	I1sa	I2sa	I3sa	I4	Total
FER	**1**	**1**	**1**	**1**	**3**	**1**	**1**	**1.3**
CL ssr	1	1	1	3	5	3	1	2.1
LIT nsc	4	4	1	3	2	1	1	2.3
LIT ml	4	4	2	2	3	2	2	2.7
LIT ssr	7	6	3	5	5	3	3	4.6
ADL(1,0) ssr	6	6	8	5	5	8	8	6.6
CL ml	8	8	6	8	8	6	6	7.1
ADL(1,0) ml	8	8	7	7	7	7	7	7.3
	Out-of-sample							
	I1	I2	I3	I1sa	I2sa	I3sa	I4	Total
CL ml	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1.0**
LIT nsc	1	1	2	1	1	2	2	1.4
LIT ml	2	2	3	2	2	3	3	2.4
CL ssr	5	5	3	5	5	3	3	4.1
FER	5	5	5	5	5	5	5	5.0
ADL(1,0) ml	5	5	6	4	5	6	6	5.3
ADL(1,0) ssr	7	6	7	7	6	7	7	6.7
LIT ssr	8	8	8	8	8	8	8	8.0

Table 16: Ranking (adjusted for non admissible solutions) by different DGPs for disturbances.

	In-sample period							
	C1	C5	C9	F	L1	L5	L9	Total
CL ssr	**1**	**1**	**1**	**2**	**2**	**3**	**4**	**2.0**
FER	2	2	2	3	3	4	4	2.9
LIT ml	2	3	5	5	5	4	2	3.7
LIT nsc	3	4	4	5	5	4	1	3.7
CL ml	5	6	5	5	5	3	5	4.9
LIT ssr	3	3	6	6	6	6	4	4.9
ADL(1,0) ml	5	5	7	7	7	7	6	6.3
ADL(1,0) ssr	4	4	8	8	8	8	7	6.7
	Out-of-sample							
	C1	C5	C9	F	L1	L5	L9	Total
CL ssr	**3**	**4**	**4**	**2**	**2**	**1**	**5**	**3.0**
CL ml	1	1	1	5	4	5	5	3.1
LIT nsc	6	6	4	4	4	2	1	3.9
FER	5	5	6	2	5	4	4	4.4
LIT ml	6	6	5	5	5	4	2	4.7
ADL(1,0) ml	2	2	3	7	6	7	7	4.9
ADL(1,0) ssr	4	4	7	6	7	6	6	5.7
LIT ssr	6	6	8	8	8	7	3	6.6