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by Giacomo Sbrana and Andrea Silvestrini

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RANDOM SWITCHING EXPONENTIAL SMOOTHING AND INVENTORY FORECASTING*

by Giacomo Sbrana§ and Andrea Silvestrini§§

Abstract

Exponential smoothing models are an important prediction tool in macroeconomics, finance and business. This paper presents the analytical forecasting properties of the random coefficient exponential smoothing model in the multiple source of error framework. The random coefficient state-space representation allows for switching between simple exponential smoothing and the local linear trend. Therefore it is possible to control, in a flexible manner, the random changing dynamic behaviour of the time series. The paper establishes the algebraic mapping between the state-space parameters and the implied reduced form ARIMA parameters. In addition, it shows that parametric mapping surmounts the difficulties that are likely to emerge in a direct estimatation of the random coefficient state-space model. Finally, it presents an empirical application comparing the forecast accuracy of the suggested model vis-à-vis other benchmark models, both in the ARIMA and in the Exponential Smoothing class. Using time series relative to wholesalers' inventories in the USA, the out-of-sample results show that the reduced form of the random coefficient exponential smoothing model tends to be superior to its competitors.

JEL Classification: C22, C53.
Keywords: exponential smoothing, ARIMA, inventory, forecasting.

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1 Introduction[1]

Exponential smoothing models represent an important prediction tool both in macroeconomics, finance and business.

In macroeconomics, exponential smoothing is popular and widely employed due to its simplicity and ability to capture nonstationarity. This type of process has a long tradition and it is one of the most recommended method in forecasting time series. The optimal properties of the simple exponential smoothing were first discussed in Muth (1960). The exponential smoothing became the cornerstone process at the origin of the rational expectations theory as in Muth (1961). Since then, several authors decided to employ this model. For example, Nelson and Schwert (1977) claimed that simple exponential smoothing is the best forecasting process, outperforming other univariate processes, in modeling the inflation rate. Similar results have been achieved more recently by Stock and Watson (2007).

Exponential smoothing is not only employed in macro, but also in business and finance. In finance, this model is widely used to produce forecasts of volatilities of financial data by the RiskMetrics methodology. This well known technique was developed by J.P. Morgan to perform volatility prediction and is extremely popular nowadays. See Sbrana and Silvestrini (2013) for a recent application to risk evaluation.

In business analysis, exponential smoothing models are widely employed in supply chain management and forecasting given their simplicity, robustness and accuracy (see Gardner, 2006; Dekker et al., 2004; Fliedner and Lawrence, 1995; Fliedner, 1999; Moon et al., 2012, 2013; Widiarta et al., 2009). This research field has gained increased interest because the adoption of an effective forecasting approach has important consequences not only on the production process itself but also on the proper functioning of the entire supply chain.

In general, based on the dynamic properties of the time series, a relevant issue often faced by researchers and practitioners is selecting the specific exponential smoothing

[1]While assuming the scientific responsibility for any errors in the paper, the authors wish to thank Giuseppe Grande, Lyudmila Grigoryeva and Juan-Pablo Ortega for useful suggestions and discussion. The paper is the responsibility of its authors and the opinions expressed here do not necessarily reflect those of the Bank of Italy or the Eurosystem.

model. For instance, the choice between adopting a local linear trend (trend exponential smoothing) and a simple exponential smoothing is usually driven by the detection (or by the absence) of a trend in the data. Nevertheless, the trend dynamics of a series is not necessarily constant over time, and may vary over the business cycle.

To deal with this issue, the time series literature has suggested some state-space alternatives, such as the damped trend exponential smoothing, whose main feature consists of adding an autoregressive (damping) parameter into the state-space (see Gardner and McKenzie, 1988, 1989 and 2011). Damped trend exponential smoothing models have gained importance in empirical studies due to their remarkable forecasting properties. This is confirmed by Armstrong (2006), who recommends these models for reducing forecasting error. Likewise, Li, Disney and Gaalman (2014) demonstrate the importance of the damped trend forecasting in the supply chain, inventory and operations management fields.

Recently, McKenzie and Gardner (2010) have proposed a random coefficient state-space model, which is akin to the damped trend exponential smoothing. This model introduces further flexibility as it allows for a stochastic mixture of standard linear trend and simple exponential smoothing. However, the authors consider a single noise driving both the trend and the slope of the state-space formulation. This is an assumption which is relaxed hereafter by adopting a more general unobserved components framework (see the discussion in Harvey, 2006). More specifically, this paper provides the analytical forecasting properties of the random coefficient state-space model in the more general multiple source of error context. In this framework, it establishes the algebraic mapping between the state-space parameters and the implied random coefficient ARIMA parameters (and vice versa).[2] Relying on this parametric mapping, it is proposed a procedure that simply requires estimating an ARIMA(1,1,2) model and then deriving analytically the random coefficient state-space parameters, keeping the optimal properties (consistency and asymptotic normality) of the maximum likelihood estimator for the ARIMA models. This represents a practical improvement due to the difficulties that are likely to emerge in estimating directly the random coefficient state-space model using standard

[2]The idea of expressing linear exponential smoothing recursions in terms of their reduced ARIMA form dates back to Box and Jenkins (1976).

maximum likelihood techniques.

Another feature of interest is the out-of-sample predicting performance of the random coefficient ARIMA reduced form model, which is evaluated by conducting an extensive forecast experiment focusing on disaggregate monthly inventory time series of merchant wholesalers in the U.S.A. It should be stressed that the out-of-sample evaluation period includes the global financial crisis.

The interest in US inventory forecasting stems from the fact that inventory movements at aggregate level play a key role in business cycle fluctuations (Blinder and Maccini, 1991a, 1991b). In fact, despite making up only a relatively small fraction of fixed investment and GDP, inventories significantly contribute to the volatility of real GDP growth; in addition, Figure B.1 shows the positive association between industrial production and inventory investment in the U.S.A. over the past two decades (on this latter issue, the interested reader is referred to Wen, 2005).

The empirical results of the forecast experiment seem promising since the out-of-sample forecasts produced by the random coefficient ARIMA are more accurate (in terms of Mean Squared Forecast Error) than those of the competitors, both at short and at longer lead times.

The remainder of the paper proceeds as follows. The main results are contained in Section 2, which provides the algebraic relations between the state-space and the implied reduced form ARIMA parameters. Section 3 presents an empirical application dealing with inventory forecasting in the U.S.A., in which the relative performance of the random coefficient ARIMA model is evaluated with respect to relevant benchmark models belonging to the ARIMA class and to the Exponential Smoothing single source of error family. Section 4 concludes.

2 The random coefficient state-space model

2.1 The multiple source of error framework

Consider the following random coefficient state-space model with additive noises (errors):

$$\begin{aligned} y_t &= l_{t-1} + A_t b_{t-1} + \epsilon_t \\ l_t &= l_{t-1} + A_t b_{t-1} + \eta_t \\ b_t &= A_t b_{t-1} + \xi_t \end{aligned} \tag{1}$$

Where $\{y_t\}$ is the observed time series, $\{l_t\}$ is its level (or stochastic trend), $\{b_t\}$ is the slope of its stochastic trend, and $t = 1, 2, \ldots, N$ is the number of observations. This is a standard state-space representation except that, in all the equations, the term A_t represents a sequence of independent, identically distributed binary random variates with probability $P(A_t = 1) = \phi$ and probability $P(A_t = 0) = (1 - \phi)$.

It is assumed that the noises have zero mean and are uncorrelated, that is:

$$cov \begin{pmatrix} \epsilon_t \\ \eta_t \\ \xi_t \end{pmatrix} = \begin{pmatrix} \sigma_\epsilon^2 & 0 & 0 \\ 0 & \sigma_\eta^2 & 0 \\ 0 & 0 & \sigma_\xi^2 \end{pmatrix} \tag{2}$$

These variances are also defined structural parameters (see Harvey, 1989).

Note that equations (1) and (2) represent the generalization of the random coefficient state-space models as in McKenzie and Gardner (2010) to the multiple source of error framework (given the three uncorrelated noises characterising the dynamics of y_t).[3] When $A_t = \phi$ this state-space representation collapses to the damped trend model in the multiple source of error form.

The random coefficient state-space model is particularly flexible since it allows for a mixture of local linear trend and simple exponential smoothing models. This feature is not only appealing from a modeling viewpoint, but it is also in line with Brown (1963),

[3]The hypothesis of uncorrelated errors can be relaxed. However, for the sake of simplicity of the algebraic calculations we keep the noises uncorrelated.

who argued that the parameters of the model may change from one segment to another as processes are thought to be *locally constant*.

To better understand this point and its relevance in empirical analysis, Figure B.2 shows a simulated time series for the model (1) and (2), with 160 observations. The series is generated such that every 20 observations the model switches from a simple exponential smoothing (that is $A_t = 0$ for the intervals: 0-20; 40-60; 80-100; 120-140) to a local linear trend (that is $A_t = 1$ for the intervals: 20-40; 60-80; 100-120; 140-160). Indeed, the changing behavior of the series represents a relevant feature since it adapts to the switching dynamics of many economic and financial time series.

In what follows some algebraic steps are needed before showing how the structural parameters determine the forecasting properties of the model in its stationary form. More specifically, these algebraic steps are instrumental for providing the exact link between the parameters of the state-space model in (1) and (2) and those of its stationary ARMA form.

2.2 The mapping between the structural and the ARMA parameters

The stationary representation of the process (1) with (2) can be derived by taking the first differences, such that:

$$z_t = y_t - y_{t-1} = l_{t-1} - l_{t-2} + A_t b_{t-1} - A_{t-1} b_{t-2} + \epsilon_t - \epsilon_{t-1} = \epsilon_t - \epsilon_{t-1} + \eta_{t-1} + A_t b_{t-1}$$

Moreover:

$$\begin{aligned}(1 - A_t L) z_t &= \epsilon_t - \epsilon_{t-1} + \eta_{t-1} + A_t b_{t-1} - A_t \epsilon_{t-1} + A_t \epsilon_{t-2} - A_t \eta_{t-2} - A_t A_{t-1} b_{t-2} = \\ &= \epsilon_t - \epsilon_{t-1} - A_t \epsilon_{t-1} + A_t \epsilon_{t-2} + \eta_{t-1} - A_t \eta_{t-2} + A_t \xi_{t-1} \qquad (3)\end{aligned}$$

where L is the lag operator (i.e., $L z_t = z_{t-1}$). The last expression holds since $A_t b_{t-1} - A_t A_{t-1} b_{t-2} = A_t \xi_{t-1}$. Therefore equation (3) is a random coefficient ARIMA(1,1,2) model, that is a mixture of two ARIMA models. More specifically, an ARIMA(0,2,2)

$$(1 - L) z_t = \epsilon_t - 2\epsilon_{t-1} + \epsilon_{t-2} + \eta_{t-1} - \eta_{t-2} + \xi_{t-1}$$

with probability ϕ and an ARIMA(0,1,1)

$$z_t \quad = \quad \epsilon_t - \epsilon_{t-1} + \eta_{t-1}$$

with probability $(1 - \phi)$.

The following Proposition further clarifies the dynamic properties of the stationary process z_t.

PROPOSITION 1. *Given (1) and (2), the autocovariances of z_t are:*

$$\begin{aligned} E(z_t z_t) &= 2\sigma^2_\epsilon + \sigma^2_\eta + \sum_{i=1}^{\infty} \phi^i \sigma^2_\xi = 2\sigma^2_\epsilon + \sigma^2_\eta + \frac{\phi}{(1-\phi)}\sigma^2_\xi \\ E(z_t z_{t-1}) &= -\sigma^2_\epsilon + \frac{\phi^2}{(1-\phi)}\sigma^2_\xi \\ E(z_t z_{t-2}) &= \frac{\phi^3}{(1-\phi)}\sigma^2_\xi \\ E(z_t z_{t-n}) &= \frac{\phi^{n+1}}{(1-\phi)}\sigma^2_\xi = \phi^{n-2} E(z_t z_{t-2}) \qquad \forall n \geq 3 \end{aligned} \tag{4}$$

Proof. The proof can be found in the Appendix. □

Therefore, the resulting process for the variable y_t is an ARIMA(1,1,2) with autoregressive parameter equal to ϕ since its autocorrelation functions are $\rho(n) = \phi^{n-2}\rho(2)$ for any $n \geq 2$. Hence the z_t process can be written as:

$$(1 - \phi L)z_t = a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} \tag{5}$$

Note that the variance of a_t, i.e., σ^2_a, represents the theoretical forecast error variance of the random coefficient state-space model in (1) and (2). The same reduced form (5) holds in the single source of error case as shown by McKenzie and Gardner (2010).

Before showing the mapping of the random coefficient state-space parameters to the ARIMA parameters, it is relevant to derive the autocovariances of the right-hand side of (5).

One can see that, given (1) with (2), the autocovariances of the right-hand side of (5) are:

$$\begin{aligned}
\gamma_0 &= E[(z_t - \phi z_{t-1})^2] = (1+\phi^2)E(z_t z_t) - 2\phi E(z_t z_{t-1}) = \\
&= \sigma_\eta^2 + \phi(\sigma_\xi^2 + (\sigma_\eta^2 + \sigma_\xi^2)\phi) + 2\sigma_\epsilon^2(1+\phi+\phi^2) \\
\\
\gamma_1 &= E[(z_t - \phi z_{t-1})(z_{t-1} - \phi z_{t-2})] = \\
&= (1+\phi^2)E(z_t z_{t-1}) - \phi E(z_t z_{t-2}) - \phi E(z_{t-1} z_{t-1}) = -\sigma_\eta^2\phi - \sigma_\epsilon^2(1+\phi)^2 \\
\\
\gamma_2 &= E[(z_t - \phi z_{t-1})(z_{t-2} - \phi z_{t-3})] = E(z_t z_{t-2}) - \phi E(z_t z_{t-1}) = \phi\sigma_\epsilon^2 \\
\\
\gamma_n &= E((z_t - \phi z_{t-1})(z_{t-n} - \phi z_{t-n-1})) = \\
&= (1+\phi^2)E(z_t z_{t-n}) - \phi E(z_t z_{t-n-1}) - \phi E(z_t z_{t-n+1}) = \\
&= (1+\phi^2)\phi^{n-2}E(z_t z_{t-2}) - \phi^{n-2}E(z_t z_{t-2}) - \phi^n E(z_t z_{t-2}) = 0 \qquad \forall n \geq 3
\end{aligned} \tag{6}$$

We are now able to map the structural parameters as in (1) and (2) into the reduced form parameters in (5). This is the content of Proposition 2.

PROPOSITION 2. *Given (1) and (2), the reduced form parameters of (5) are analytical functions of the structural parameters as in what follows:*

$$\begin{aligned}
&\sigma_a^2 = \tfrac{1}{4}(2\sigma_\epsilon^2 + \sigma_\eta^2 + \sigma_\xi^2\phi + (2\sigma_\epsilon^2 + \sigma_\eta^2 + \sigma_\xi^2)\phi^2 + D\sqrt{1+\phi} + \\
&+\sqrt{2}\sqrt{-2\sigma_\epsilon^4 - 12\sigma_\epsilon^4\phi^2 - 8\sigma_\epsilon^2\sigma_\eta^2\phi^2 - 2\sigma_\eta^4\phi^2 + 4\sigma_\epsilon^2\sigma_\xi^2\phi^2 + 4\sigma_\epsilon^2\sigma_\xi^2\phi^3 - 2\sigma_\epsilon^4\phi^4 + F^2 + FD\sqrt{1+\phi}}\,) \\
\\
&\theta_2 = \tfrac{\phi\sigma_\epsilon^2}{\sigma_a^2} \\
\\
&\theta_1 = \tfrac{-\sigma_\eta^2\phi - \sigma_\epsilon^2(1+\phi)^2}{\phi\sigma_\epsilon^2 + \sigma_a^2}
\end{aligned} \tag{7}$$

with

$$D = \sqrt{\sigma_\eta^2 + (\sigma_\eta^2 + \sigma_\xi^2)\phi + 4\sigma_\epsilon^2(1+\phi)}\sqrt{\sigma_\eta^2(-1+\phi)^2 + \sigma_\xi^2\phi(1+\phi)}$$

$$F = 2\sigma_\epsilon^2 + \sigma_\eta^2 + \sigma_\xi^2\phi + (2\sigma_\epsilon^2 + \sigma_\eta^2 + \sigma_\xi^2)\phi^2$$

Proof. The proof can be found in the Appendix.[4] □

Remark 1. *Note that the suggested framework as in (1) and (2) implies the following conditions on the reduced form ARIMA model:* $\theta_2 > 0$ *and* $\theta_1 < 0$*. Indeed, the expressions as in (6) guarantee that* $\gamma_1 < 0$ *and* $\gamma_2 > 0$*.*

Remark 2. *The algebraic results are valid in general regardless of the distribution of the noises of the model (1) and (2).*

Figures B.3 and B.4 display three-dimensional and contour plots of the variance σ_a^2 as a function of γ_1 and γ_2. In particular, Figure B.3 shows the variance as a function of γ_1 and γ_2, fixing $\gamma_0 = 1$. Figure B.4 refers to the corresponding contour plot.

These expressions give full control of the theoretical variance of the random coefficient state-space model.[5] As a consequence, the minimum mean squared error (MMSE) forecasts as well as the *h-steps ahead* theoretical forecast error variance are also algebraic functions of the structural parameters.

Figures B.5 and B.7 display three-dimensional plots of θ_1 and θ_2 as a function of γ_1 and γ_2 (fixing $\gamma_0 = 1$). Figures B.6 and B.8 show the corresponding contour plots. In the graphs, it is important to note that the regions of the ARIMA parameters spanned by the model (1) and (2) are in accordance with the constraints described in Remark 1.

2.3 ARMA estimation of the random coefficient state-space model

The direct estimation of model (1) with (2) is a challenging task. Here we present a simple estimator that enjoys the same asymptotic properties of the maximum likelihood estimator for ARMA processes. It is relevant to note that the number of structural

[4]These analytical expressions are derived using Mathematica. A file containing all calculations is available upon request.

[5]An Eviews 7 program containing a Monte Carlo simulation running the whole procedure can be provided by the authors upon request. In addition, an Excel file computing the autocovariances as in (6) as well as the moving average parameters, given the structural parameters, is also available upon request.

parameters coincides with that of the reduced form. Indeed, there are four structural parameters (ϕ; σ_ϵ^2; σ_η^2; σ_ξ^2) mapping four ARIMA parameters (ϕ; θ_1; θ_2; σ_a^2). Therefore the mapping given in Proposition 2 can be reversed as shown in the following Proposition.

PROPOSITION 3. *Given (1) and (2), the structural parameters of the random coefficient state-space model can be derived as analytical functions of the reduced form parameters such that:*

$$\Lambda = \begin{bmatrix} \phi \\ \\ \sigma_\xi^2 \\ \\ \sigma_\eta^2 \\ \\ \sigma_\epsilon^2 \end{bmatrix} = \begin{bmatrix} \phi \\ \\ \frac{\sigma_a^2(\theta_2+\phi(\theta_1+\phi))(1+\phi(\theta_1+\theta_2\phi))}{\phi^3(1+\phi)} \\ \\ -\frac{\sigma_a^2(\theta_1\phi+\theta_2(1+\phi(2+\theta_1+\phi)))}{\phi^2} \\ \\ \frac{\sigma_a^2\theta_2}{\phi} \end{bmatrix} \tag{8}$$

Proof. The expression for ϕ follows from the proof of Proposition 1 (see the Appendix). The remaining parameters are derived by solving the system of three equations (the autocovariances of the right-hand side of (5)) with respect to the three variances (i.e., $\sigma_\epsilon^2; \sigma_\xi^2; \sigma_\eta^2$). That is, by solving the following system of equations:

$$\begin{aligned} \gamma_0 &= \sigma_a^2(1+\theta_1^2+\theta_2^2) \\ \gamma_1 &= \sigma_a^2(\theta_1+\theta_1\theta_2) \\ \gamma_2 &= \sigma_a^2\theta_2 \end{aligned} \tag{9}$$

Where the γ's are given in (6). $\square$

Remark 3. *It is relevant to note that the algebraic link between the parameters of the process as in (1) and those of the ARIMA(1,1,2) as in (5) is guaranteed if and only if the derived parameters in the left-hand side of (8) are all positive (this implies that* $\gamma_1 < 0$ *and* $\gamma_2 > 0$ *as noted in Remark 1). Indeed, these parameters must be positive* *by definition (see (2)). Moreover, this condition enables the indirect estimation of the parameters as in (1).*

An important consequence of the closed-form results as in Proposition 3 is the following limiting result.

THEOREM 1. *Given (1), (2) and (8). Let:*

$$\beta = \begin{bmatrix} \phi \\ \theta_1 \\ \theta_2 \\ \sigma_a^2 \end{bmatrix}$$

then:

$$\hat{\Lambda} \to \Lambda$$

where $\to$ denotes convergence in probability.

In addition, if also the fourth moment of a_t is finite, then the following holds:

$$\sqrt{N}\left(\hat{\Lambda} - \Lambda\right) \Rightarrow N(0, \left(\frac{\partial \Lambda}{\partial \beta}\right)^T \Sigma \left(\frac{\partial \Lambda}{\partial \beta}\right)) \tag{10}$$

where $\Rightarrow$ denotes convergence in distribution to the Gaussian and T denotes the transpose. In addition:

$$\Sigma = \begin{bmatrix} c_1 & c_2 & c_3 & 0 \\ c_2 & c_4 & c_5 & 0 \\ c_3 & c_5 & c_6 & 0 \\ 0 & 0 & 0 & 2\sigma_a^4 \end{bmatrix}$$

with[6]

$$c_1 = -\frac{(-1+\phi^2)(1+\phi(\theta_1+\theta_2\phi))^2}{(\theta_2+\phi(\theta_1+\phi))^2}$$

$$c_2 = -\frac{(-1+\theta_2)(1+\theta_2+\theta_1\phi)(-1+\phi^2)\ (1+\phi(\theta_1+\theta_2\phi))}{(\theta_2+\phi(\theta_1+\phi))^2}$$

$$c_3 = -\frac{(-1+\theta_2)(\theta_1+\phi+\theta_2\phi)(-1+\phi^2)\ (1+\phi(\theta_1+\theta_2\phi))}{(\theta_2+\phi(\theta_1+\phi))^2}$$

$$c_4 = -\frac{(-1+\theta_2)(1+\theta_2+2\theta_1(1+\theta_2)\phi+(-1+2\theta_1^2+\theta_2+3\theta_2^2+\theta_2^3)\phi^2+2\theta_1\theta_2(1+\theta_2)\phi^3+(1+\theta_1^2(-1+\theta_2)+\theta_2)\phi^4)}{(\theta_2+\phi(\theta_1+\phi))^2}$$

$$c_5 = -\frac{(-1+\theta_2)(\theta_1^3\phi^2+(-1+\theta_2)(1+\theta_2)^2\phi(-1+\phi^2)+\theta_1(1+\theta_2\ \phi^2)^2+\theta_1^2(1+\theta_2)(\phi+\phi^3))}{(\theta_2+\phi(\theta_1+\phi))^2}$$

$$c_6 = -\frac{(-1+\theta_2)(2\theta_1(1+\theta_2)\phi(1+\theta_2\phi^2)+\theta_1^2(1+\theta_2(-1+2\phi^2))+(1+\theta_2)(\phi^2+\theta_2(\theta_2-(-2+\theta_2)\phi^2+\theta_2\phi^4)))}{(\theta_2+\phi(\theta_1+\phi))^2}$$

and

$$\left(\frac{\partial\Lambda}{\partial\beta}\right) = \begin{bmatrix} 1 & c & \frac{\sigma_a^2(\theta_1\phi+\theta_2(2+(2+\theta_1)\phi))}{\phi^3} & -\frac{\sigma_a^2\theta_2}{\phi^2} \\ 0 & \frac{\sigma_a^2(1+\theta_2+2\theta_1\phi+(1+\theta_2)\phi^2)}{\phi^2(1+\phi)} & -\frac{\sigma_a^2(1+\theta_2)}{\phi} & 0 \\ 0 & \frac{\sigma_a^2(1+2\theta_2\phi^2+\phi^4+\theta_1(\phi+\phi^3))}{\phi^3(1+\phi)} & -\frac{\sigma_a^2(1+\phi(2+\theta_1+\phi))}{\phi^2} & \frac{\sigma_a^2}{\phi} \\ 0 & \frac{(\theta_2+\phi(\theta_1+\phi))(1+\phi(\theta_1+\theta_2\phi))}{\phi^3(1+\phi)} & -\frac{\theta_1\phi+\theta_2(1+\phi(2+\theta_1+\phi))}{\phi^2} & \frac{\theta_2}{\phi} \end{bmatrix}$$

[6]The derivation of the matrix Σ was obtained with *Time Series 1.4.1* package of Mathematica.

with

$$c = \frac{\sigma_a^2(-3\theta_2-2(\theta_1+(2+\theta_1)\theta_2)\phi-(1+\theta_1^2+\theta_2^2+3\theta_1(1+\theta_2))\phi^2-2(1+\theta_1^2+\theta_2^2)\phi^3-(\theta_1+(-1+\theta_1)\theta_2)\phi^4)}{\phi^4(1+\phi^2)}$$

Proof. The convergence in probability of the maximum likelihood estimator for ARMA processes is shown in Brockwell and Davis (1991) (see Chapter 10, Theorem 10.8.1). Therefore this property also holds for Λ, due to the continuous mapping theorem. The asymptotic normality is also shown in Chapter 10, Brockwell and Davis (1991) (see Theorem 10.8.2). This also holds for Λ due to the Delta method, given that Λ is a simple function of β. Note that, in (10), Σ represents the asymptotic variance of the maximum likelihood estimator for ARMA processes (derived in Box and Jenkins, 1976, Chapter 7). While $\frac{\partial\Lambda}{\partial\beta}$ represents the partial derivative of Λ with respect to the vector of ARMA parameters β. $\square$

These results have important practical consequences. Indeed, one can easily estimate an ARIMA(1,1,2) model and then derive the structural parameters still relying on the optimal properties of the maximum likelihood estimator for the ARIMA processes. In the next section an empirical application using these analytical results is presented.

3 Empirical application

This section focuses on an empirical application dealing with inventory forecasting. It first describes the data and the experimental set-up; then, it discusses the forecasting results. The aim is to evaluate the relative forecasting performance of the reduced form of the random coefficient state-space model in equations (1) and (2) – which is an ARIMA(1,1,2) with restrictions on the parameter space – with respect to competitive models belonging to the ARIMA class and to the Exponential Smoothing single source of error (ETS) family (Hyndman et al., 2008).

The variables used for the purpose of our research are seasonally adjusted estimates of monthly sector-level inventories of merchant wholesalers (except manufacturers' sales branches and offices), expressed in millions of dollars, at different aggregation level. Data refer to the 4-digit North American Industry Classification System (NAICS) industry level durable (nine time series) and non-durable goods (nine time series), to the 3-digit aggregate durable and non-durable series (NAICS 423 – total durable wholesale and NAICS 424 – total non-durable wholesale) and to the aggregate 2-digit total merchant wholesalers time series (NAICS 42, total wholesale). The source of the data is U.S. Census Bureau's (`http://www.census.gov/wholesale/`).[7] For each series, 261 observations ranging from January 1992 through September 2013 are available. A full description of the dataset is provided in Table 1.

The (4-digit and 3-digit) time series plots are presented in Figure B.9. In the vertical axis, the outstanding amounts are expressed in thousands of millions of dollars.

In order to evaluate the forecasting performance of the random coefficient ARIMA model (RC-ARIMA(1,1,2)), the exercise begins by considering a group of three benchmark ARIMA models:

1. ARIMA(p,1,q) model, with $p = 1, 2, 3$; $q = 1, 2, 3$ (hence, the maximum AR and MA order is set equal to three); the standard information criteria are applied in order to select p and q (in particular, the Schwartz Information Criterion, BIC);

2. ARIMA(0,1,1) model, which is the reduced form of simple exponential smoothing;

3. ARIMA(0,2,2) model, which is the reduced form of a local linear trend model (see, e.g., Harvey, 1989).

All the models are specified (and estimated) with a constant. The data are in levels.

The set-up of the forecasting exercise is as follows. For each time series, the first in-sample used for estimation ranges from 1992/01 to 2008/12. The out-of-sample evaluation period goes from 2009/01 onwards. Consistently, in Figure B.9 the shaded areas identify the out-of-sample, which fully includes the global financial crisis. This makes the whole forecasting exercise more challenging.

The maximum forecast horizon is set to six months. Thus, $h = 1, 3, 6$-steps-ahead predictions are made for 2009/01, 2009/03, and 2009/06, using the RC-ARIMA(1,1,2) and the three benchmark ARIMA models as above.The out-of-sample forecasting accuracy of the RC-ARIMA(1,1,2) model is evaluated by its Mean Squared Forecast Error (MSFE) compared to that of a competitive model.

[7] Accessed on December 4, 2013.

For each prediction model, forecast horizon and information set, the MSFE is defined as:

$$MSFE_{t_0}^{N}(h,j) = \frac{1}{N-t_0+1}\sum_{t=t_0}^{N}(y_{t+h}-\hat{y}_{t+h|t}^{j})^2 \tag{11}$$

where y_{t+h} is the realized value of the variable at time $t+h$, t_0 and N are the first and last data point in the out-of-sample, $\hat{y}_{t+h|t}^{j}$ is the forecast made at time t at horizon $h = 1, 3, 6$ from model j. Relative MSFEs are calculated simply dividing the MSFE of the RC-ARIMA(1,1,2) model by the MSFE of one of the benchmark models. Values greater than one for the relative MSFE indicate that the MSFE produced by the random coefficient state-space model is larger than that of the competitive model. Conversely, ratios below unity indicate that random coefficient state-space model forecasts are more accurate with respect to the competitive model.

Then, the in-sample is expanded by one observation, the models are re-estimated, $h = 1, 3, 6$-steps-ahead forecasts are again produced (this time for 2009/02, 2009/04, and 2009/07) and the corresponding (relative) MSFEs are calculated. The same procedure is repeated recursively 55 times. Thereby, we get a sequence of forecast errors on which the MSFEs are based.

Each $h = 1, 3, 6$-steps-ahead prediction is evaluated over 50 observations: this means that, for instance, when considering $h = 1$-step-ahead predictions, the first forecast point is 2009/01, while the last forecast point is 2013/02. Similarly, for $h = 6$-steps-ahead predictions, the first forecast point is 2009/06, whilst the last forecast point is 2013/07.

Every time the RC-ARIMA(1,1,2) model is estimated, it is carefully checked that Remark 3 is satisfied. This guarantees that $\sigma_{\xi}^2 > 0$, $\sigma_{\eta}^2 > 0$ and $\sigma_{\epsilon}^2 > 0$. This check is repeated each time a new observation is added to the in-sample from the out-of-sample and forecasts are produced. If these constraints are not met by the estimated ARIMA(1,1,2) parameters, then the corresponding time series is excluded from the competition. In this exercise, for instance, nine time series have been discarded (S4235, S4239, S424, S4241, S4242, S4244, S4245, S4247 and S4249).

The following tables summarise the accuracy of the models, displaying the relative

MSFEs and the Diebold and Mariano (1995) forecast accuracy test results. Table 2 refers to the one-step-ahead forecast results. The three and six-steps ahead projections results are presented in Tables 3, and 4, respectively.

All the tables have the same structure. Each row corresponds to a single inventory time series. The second column reports the ratio of MSFE for the RC-ARIMA(1,1,2) to the MSFE for the ARIMA(p,1,q); the third column refers to the ratio of MSFE for RC-ARIMA(1,1,2) vs ARIMA(0,1,1), while the fourth column refers to the ratio of MSFE for RC-ARIMA(1,1,2) vs ARIMA(0,2,2). For completeness' sake, results relative to the nine items excluded from the forecasting competition are reported in the bottom part of the tables.

The last three columns report the Diebold and Mariano (DM) test results. In particular, column five compares the performance of RC-ARIMA(1,1,2) vs ARIMA(p,1,q); column six refers to the comparison between RC-ARIMA(1,1,2) and ARIMA(0,1,1); column seven refers to the comparison between RC-ARIMA(1,1,2) and ARIMA(0,2,2). The basis of the DM test statistics is the sample mean of the observed loss differential series over all the 50 forecast points. In this application, a quadratic loss function has been used. Under the null hypothesis of equal predictive accuracy (i.e., equal expected loss) the limiting distribution of the test statistics is standard Normal. A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model.

In summary, what emerges from Tables 2 to 4 is the following:

- The most striking result is that RC-ARIMA(1,1,2) model performs clearly better than the ARIMA(0,1,1) and ARIMA(0,2,2) benchmarks, at all forecast horizons. The ARIMA(0,2,2) model is never successful compared to the RC-ARIMA(1,1,2). The ARIMA(0,1,1) has better performance only for the S4248 series, when $h = 6$. Therefore, substantial improvements can be achieved by using the RC-ARIMA(1,1,2) model, which allows for switching between the simple exponential smoothing and the local linear trend models and therefore provides with a more flexible parameterization of the changing dynamic behavior of the time series;

- When the ARIMA(p,1,q) benchmark is considered, results are less clear-cut. The RC-ARIMA(1,1,2) model is slightly superior at short horizons ($h = 1, 3$), whereas at longer horizons ($h = 6$) the reverse is true. However, in general most of the times the DM test statistics is not significant. This is largely expected. Indeed, when considering the ARIMA(p,1,q) benchmark, standard model selection criteria based on the log-likelihood function (with a penalty term for the number of parameters in the model) such as the BIC are used to select the "best" AR and MA order.[8] Yet, in-sample information criteria based on the penalized log-likelihood do not always constitute the most reliable indicators for choosing the best forecasting model;

- The ranking of the RC-ARIMA(1,1,2) relative to the ARIMA(p,1,q), ARIMA(0,1,1) and ARIMA(0,2,2) models does not appear to depend on the forecast horizon;

- Looking at the excluded items, the DM test results suggest that most of the times there are no major differences in predictive ability between pairs of models.

Next, the forecasting performance of the RC-ARIMA(1,1,2) is evaluated with respect to competitive models belonging to the Exponential Smoothing single source of error (ETS) family. Although it is well known that ARIMA models and the ETS family overlap and are complementary (see the discussion in Hyndman et al., 2008), ETS models have been shown to perform very well in business forecasting and are now a benchmark in most forecasting competitions.

Specifically, three models are considered (the same taxonomy as in Hyndman et al., 2008, is used in what follows):

1. $ETS(A, A_d, N)$: this is the damped trend as, for instance, in Gardner and McKenzie (2011); it has an ARIMA(1,1,2) reduced form;

2. $ETS(A, A, N)$: this is the additive Holt's linear method, which has an ARIMA(0,2,2) reduced form;

3. $ETS(A, N, N)$: this is the simple exponential smoothing, which has an ARIMA(0,1,1) reduced form.

[8] Actually, this procedure appears to be employed by most econometric software packages.

The $ETS(A, A_d, N)$ damped trend is the most general specification. Since the pioneering contributions of Gardner and McKenzie (1988, 1989), damped trend exponential smoothing gained importance due to its remarkable forecasting properties. Therefore, the damped trend is often considered as a benchmark model to beat in forecasting competitions.

The set-up of the forecasting exercise is as before. To fit the ETS models and produce forecasts, the ETS exponential smoothing built-in procedure provided in EViews 8 is used.[9] The results are presented in Tables from 5 to 7.

Overall, the RC-ARIMA(1,1,2) model shows good forecasting ability, performing better than the ETS benchmarks at all forecast horizons. According to the DM test results, the differences in the forecast error quadratic loss differential are further enhanced, as shown by the statistical significance of these statistics.

Interestingly, looking in more detail to Tables 5 to 7 reveals that:

- In general, the RC-ARIMA(1,1,2) model is clearly overperforming the three ETS benchmarks; this is also evident when the comparison is made with the $ETS(A, A_d, N)$;
- The $ETS(A, A, N)$) and $ETS(A, N, N)$ models are rapidly outperformed by the RC-ARIMA(1,1,2), which is unsurprising in the light of the swings observed by most of the inventory series during the out-of-sample evaluation period. Considering the damped trend version $ETS(A, A_d, N)$ does not seem to help in this respect, given that the DM test results reveal that even this model is clearly outperformed by the RC-ARIMA(1,1,2), especially at very short horizons;
- Also in this case, the ranking of the RC-ARIMA(1,1,2) with respect to its competitors does not appear to depend on the chosen forecast horizon;
- Focusing on the excluded items, according to the DM test, no major differences in predictive ability are detected.

[9]The Average Mean Square Error is the objective function, meaning that the estimated parameter values and initial state values minimize the Average Mean Square Error of the h-step forecasts of the specified ETS model.

Summing up, this application provides some evidence that the proposed ARIMA model is able to outperform a variety of benchmark competitors, both in the ARIMA and in the ETS class, on a time horizon ranging from one up to six months ahead. As expected, the accuracy of forecasts produced by the RC-ARIMA(1,1,2) model tends to be comparable (although slightly superior) to that of ARIMA(p,1,q) models in which the AR and MA orders are selected by an in-sample information criterion. Moreover, the RC-ARIMA(1,1,2) seems to outperform the considered ETS models in most of the cases.

It should be noted, nevertheless, that these encouraging results are only valid when some specific constraints hold (see Remark 3). This condition should be checked empirically when using data. Indeed, this has evident consequences in our empirical exercise: when choosing an ARIMA model, if the ARIMA(1,1,2) process has (estimated) parameters respecting Remark 3, then it might represent a strong candidate in forecasting inventories. If, on the other hand, conditions in Remark 3 are not met, then this model might not be a good candidate. This should not prevent from using the forecasts of the ARIMA(1,1,2) process. However, if the ARIMA(1,1,2) does not meet Remark 3, our results are not as remarkable as for the RC-ARIMA case.

4 Conclusions

This paper has investigated the analytical properties of the random coefficient state-space model with multiple source of error, generalizing the results provided by McKenzie and Gardner (2010), who introduced this model as a variant of the damped trend exponential smoothing in the single source of error class.

The random coefficient state-space model allows for a stochastic mixture of simple exponential smoothing and local linear trend time series models. It is akin to the damped trend exponential smoothing, in which an autoregressive-damping parameter is introduced to damp the trend component. Yet, differently from the damped trend exponential smoothing, the autoregressive-damping parameter is not constant but is instead a random coefficient governing the persistence of the trend, which is allowed to change suddenly. Indeed, it is widely recognised that trend persistence is not a stable time series property, rather it may change over the phases of the business cycle, even abruptly. Accordingly, this specification accommodates unsmooth changes of the gradient of the trend, adapting very well to the switching behavior of many sales and inventories time series (especially during crisis periods).

One contribution of this paper is providing the algebraic mapping between the state-space parameters and the implied ARIMA parameters. Relying on this parametric mapping, it is proposed a procedure that requires simply to estimate an ARIMA(1,1,2) model and then to derive the random coefficient state-space parameters, keeping the optimal properties (consistency and asymptotic normality) of the maximum likelihood estimator for the ARIMA models. This is an improvement to the literature, due to the difficulties that are likely to emerge in estimating directly the random coefficient state-space model. Yet, the indirect estimation of the random coefficient state-space parameters is feasible if and only if Remark 3 is met. This represents a guideline for modelers: when the expressions as in (8) are all positive the ARIMA(1,1,2) can be considered as reparametrization of the random switching whose parameters can be easily derived. When the reverse is true, the link with the ARIMA model is not legitimate; this represents a signal that the data may not follow the stochastic dynamics as described in (1). These criteria should be employed by practitioners in empirical analysis.

Another feature of interest is the out-of-sample predicting performance of the RC-ARIMA reduced form model, which is evaluated by conducting an extensive forecast experiment focusing on disaggregate monthly inventory time series of merchant wholesalers in the U.S.A. The out-of-sample evaluation period includes the global financial crisis. The results are encouraging since the forecasts produced by the ARIMA model are overall more accurate than those of several relevant benchmark models belonging both to the ARIMA class and to the Exponential Smoothing single source of error family. These results hold true both at short and at longer lead times.

Admittedly, further research is needed to explore the forecasting capabilities of the RC-ARIMA(1,1,2) model, which, however, deems in our view to be considered as a useful prediction tool in macroeconomics, finance and business.

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APPENDIX

A Proof of Proposition 1

It is relevant to expand equation (3) in order to derive the recursion for z_t. That is, how z_t is generated by the three noises of the model (1) and by the random coefficient parameter A_t:

$$\begin{aligned} z_t &= \epsilon_t - (1+A_t)\epsilon_{t-1} + A_t\epsilon_{t-2} + \eta_{t-1} - A_t\eta_{t-2} + A_t\xi_{t-1} + \\ &\quad + A_t(\epsilon_{t-1} - (1+A_{t-1})\epsilon_{t-2} + A_{t-1}\epsilon_{t-3} + \eta_{t-2} - A_{t-1}\eta_{t-3} + A_{t-1}\xi_{t-2} + A_{t-1}z_{t-2}) = \\ &= \epsilon_t - \epsilon_{t-1} - A_tA_{t-1}\epsilon_{t-2} + A_tA_{t-1}\epsilon_{t-3} + \eta_{t-1} - A_tA_{t-1}\eta_{t-3} + A_t\xi_{t-1} + \\ &\quad + A_tA_{t-1}\xi_{t-2} + A_tA_{t-1}z_{t-2} \end{aligned}$$

In addition, we have that:

$$\begin{aligned} A_tA_{t-1}z_{t-2} &= A_tA_{t-1}\epsilon_{t-2} - A_tA_{t-1}\epsilon_{t-3} - A_tA_{t-1}A_{t-2}A_{t-3}\epsilon_{t-4} + \\ &\quad + A_tA_{t-1}A_{t-2}A_{t-3}\epsilon_{t-5} + A_tA_{t-1}\eta_{t-3} - A_tA_{t-1}A_{t-2}A_{t-3}\eta_{t-5} + \\ &\quad + A_tA_{t-1}A_{t-2}\xi_{t-3} + A_tA_{t-1}A_{t-2}A_{t-3}\xi_{t-4} + A_tA_{t-1}A_{t-2}A_{t-3}z_{t-4} \end{aligned}$$

such that the expression for z_t reduces to:

$$\begin{aligned} z_t &= \epsilon_t - \epsilon_{t-1} - A_tA_{t-1}A_{t-2}A_{t-3}\epsilon_{t-4} + A_tA_{t-1}A_{t-2}A_{t-3}\epsilon_{t-5} + \\ &\quad + \eta_{t-1} - A_tA_{t-1}A_{t-2}A_{t-3}\eta_{t-5} + A_t\xi_{t-1} + A_tA_{t-1}\xi_{t-2} + A_tA_{t-1}A_{t-2}\xi_{t-3} + \\ &\quad + A_tA_{t-1}A_{t-2}A_{t-3}\xi_{t-4} + A_tA_{t-1}A_{t-2}A_{t-3}z_{t-4} \end{aligned}$$

The generic recursion for z_t is as follows:

$$\begin{aligned} z_t &= \epsilon_t - \epsilon_{t-1} - A_tA_{t-1}\cdots A_{t-(2n-1)}\epsilon_{t-2n} + A_tA_{t-1}\cdots A_{t-(2n-1)}\epsilon_{t-(2n+1)} \\ &\quad + \eta_{t-1} - A_tA_{t-1}\cdots A_{t-(2n-1)}\eta_{t-(2n+1)} + A_t\xi_{t-1} + A_tA_{t-1}\xi_{t-2} + \\ &\quad + A_tA_{t-1}A_{t-2}\xi_{t-3} + \cdots + A_tA_{t-1}\cdots A_{t-(2n-1)}\xi_{t-2n} + A_tA_{t-1}\cdots A_{t-(2n-1)}z_{t-2n} \\ &\quad n = 1, 2, 3, \ldots \end{aligned}$$

Note that $E[A_t^n] = \phi$. In addition, $E(A_t A_{t-1}) = \phi^2$ which can be generalized as $E(A_t A_{t-1} A_{t-2} \cdots A_{t-n}) = \phi^n$. Therefore, provided that $\phi < 1$, for $n \to \infty$ the autocovariances of z_t are:

$$
\begin{aligned}
E(z_t z_t) &= 2\sigma_\epsilon^2 + \sigma_\eta^2 + \sum_{i=1}^{\infty} \phi^i \sigma_\xi^2 = 2\sigma_\epsilon^2 + \sigma_\eta^2 + \frac{\phi}{(1-\phi)}\sigma_\xi^2 \\
E(z_t z_{t-1}) &= -\sigma_\epsilon^2 + \frac{\phi^2}{(1-\phi)}\sigma_\xi^2 \\
E(z_t z_{t-2}) &= \frac{\phi^3}{(1-\phi)}\sigma_\xi^2 \\
E(z_t z_{t-n}) &= \phi^{n-2} E(z_t z_{t-2}) = \frac{\phi^{n+1}}{(1-\phi)}\sigma_\xi^2 \qquad \forall n \geq 2 \qquad (12)
\end{aligned}
$$

B Proof of Proposition 2

Let z_t be an invertible moving average process of order two such that:

$$z_t = a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2}$$

Where a_t is white noise process with variance σ_a^2. Considering the following autocovariance functions: $E(z_t^2) = \gamma_0$, $E(z_t z_{t-1}) = \gamma_1$, $E(z_t z_{t-2}) = \gamma_2$. The moving average parameters can be recovered solving the following system of three equations (autocorrelations):

$$
\begin{aligned}
\frac{\gamma_2}{\gamma_0} &= \frac{\theta_2}{(1+\theta_1^2+\theta_2^2)} \\
\frac{\gamma_1}{\gamma_0} &= \frac{\theta_1+\theta_1\theta_2}{(1+\theta_1^2+\theta_2^2)} \\
\sigma_a^2 &= \frac{\gamma_0}{(1+\theta_1^2+\theta_2^2)}
\end{aligned}
$$

These equations represent respectively the second and first order autocorrelations of the process and the variance of a_t.

First, the following analytical solutions can be easily obtained:

$$
\begin{aligned}
\theta_2 &= \frac{\gamma_2}{\sigma_a^2} \\
\theta_1 &= \frac{\gamma_1}{(\sigma_a^2+\gamma_2)}
\end{aligned}
$$

Secondly, substituting these solutions in the last equation of the system, the following quartic equation in x (with $x = \sigma_a^2$) can be obtained:

$$\frac{x^4 + (2\gamma_2 - \gamma_0)x^3 + (2\gamma_2^2 - 2\gamma_2\gamma_0 + \gamma_1^2)x^2 + (2\gamma_2^3 - \gamma_2^2\gamma_0)x + \gamma_2^4}{x(x+\gamma_2)^2} = 0$$

This equation has four different solutions. Yet, the only solution leading to the invertible process[10] is:

$$\sigma_a^2 = \frac{1}{4}\left(\gamma_0 - 2\gamma_2 + G + \sqrt{2}\sqrt{\gamma_0^2 + \gamma_0 G - 2\left(\gamma_1^2 + \gamma_2\left(2\gamma_2 + G\right)\right)}\right)$$

with:

$$G = \sqrt{\left(\gamma_0 - 2\gamma_1 + 2\gamma_2\right)\left(\gamma_0 + 2\gamma_1 + 2\gamma_2\right)}$$

and:

$$\theta_2 = \frac{4\gamma_2}{\left(\gamma_0 - 2\gamma_2 + G + \sqrt{2}\sqrt{\gamma_0^2 + \gamma_0 G - 2\left(\gamma_1^2 + \gamma_2\left(2\gamma_2 + G\right)\right)}\right)}$$

$$\theta_1 = \frac{4\gamma_1}{\left(\gamma_0 + 2\gamma_2 + G + \sqrt{2}\sqrt{\gamma_0^2 + \gamma_0 G - 2\left(\gamma_1^2 + \gamma_2\left(2\gamma_2 + G\right)\right)}\right)}$$

[10]A process with roots of the characteristic function that lie outside the unit circle (i.e. $\theta_2 - \theta_1 < 1$;$-1 < \theta_2 < 1$).

TABLES and FIGURES

Table 1: Data description: US inventories

NAICS CODE	DATA ITEM	NAICS DESCRIPTION (sub-parts indicated by one or more leading dots)
S42	Inventories	Total Merchant Wholesalers, Except Manufacturers' Sales Branches and Offices
S423	Inventories	.Durable Goods
S4231	Inventories	..Motor Vehicle & Motor Vehicle Parts & Supplies
S4232	Inventories	..Furniture & Home Furnishings
S4233	Inventories	..Lumber & Other Construction Materials
S4234	Inventories	..Professional & Commercial Equipment & Supplies
S4235	Inventories	..Metals & Minerals, Except Petroleum
S4236	Inventories	..Electrical & Electronic Goods
S4237	Inventories	..Hardware, & Plumbing & Heating Equipment & Supplies
S4238	Inventories	..Machinery, Equipment, & Supplies
S4239	Inventories	..Miscellaneous Durable Goods
S424	Inventories	.Non-durable Goods
S4241	Inventories	..Paper & Paper Products
S4242	Inventories	..Drugs & Druggists' Sundries
S4243	Inventories	..Apparel, Piece Goods, & Notions
S4244	Inventories	..Grocery & Related Products
S4245	Inventories	..Farm Product Raw Materials
S4246	Inventories	..Chemicals & Allied Products
S4247	Inventories	..Petroleum & Petroleum Products
S4248	Inventories	..Beer, Wine, & Distilled Alcoholic Beverages
S4249	Inventories	..Miscellaneous Nondurable Goods

Table 2: US inventories results – One-step-ahead forecasts – ARIMA benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,2,2)	DM Test RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,2,2)
S42	1.0852	0.6032	0.9504	0.6836	**-2.6935**	-1.0502
S423	0.9389	0.4849	0.9446	-0.6020	**-3.0504**	-0.9466
S4231	1.0157	0.9843	0.9178	0.2147	-0.2802	**-1.8754**
S4232	0.8665	0.6789	0.8348	-1.4714	**-2.4870**	**-2.2998**
S4233	1.0284	0.6994	0.8830	0.5261	**-2.0208**	-1.3062
S4234	1.0233	0.9464	0.8929	0.3010	-0.5185	-1.4342
S4236	1.0034	0.6943	0.8912	0.1081	**-2.0310**	-1.6263
S4237	0.9875	0.6860	0.9095	-0.3511	**-2.4681**	**-1.7711**
S4238	0.9789	0.6543	0.9467	-0.5911	**-3.1448**	-1.0433
S4243	0.8400	0.8754	0.8554	**-2.3933**	**-1.9765**	**-2.6348**
S4246	0.9353	0.8938	0.8394	-1.0814	-1.2145	**-1.8469**
S4248	1.0931	1.0840	1.0201	1.1137	0.9847	0.3310
			EXCLUDED ITEMS			
S4235	0.8517	0.6002	0.9249	-1.2227	**-2.0431**	-0.6058
S4239	1.0603	1.0553	0.9909	1.1566	1.1075	-0.1972
S424	0.9825	0.9973	0.9445	-0.1833	-0.0364	-0.9812
S4241	0.9708	0.9490	1.0034	-0.8955	-1.3877	0.0484
S4242	0.9895	1.0629	0.9990	-0.0600	0.8820	-0.0109
S4244	1.0083	1.0028	0.9863	0.2085	0.0701	-0.2738
S4245	0.9028	1.0472	1.0188	-1.2639	1.2075	0.4352
S4247	0.9459	1.1812	1.1658	-1.0325	**1.7811**	1.4787
S4249	0.9456	0.9723	0.9525	-0.7690	-0.3951	-0.5858

In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are: ARIMA(p,1,q), ARIMA(0,1,1) and ARIMA(0,2,2). A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Table 3: US inventories results – Three-steps-ahead forecasts – ARIMA benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,2,2)	DM Test RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,2,2)
S42	1.3898	0.5021	0.8704	**1.6903**	**-2.2595**	-1.6081
S423	0.8847	0.3521	0.8426	-0.7908	**-3.1390**	**-1.8030**
S4231	0.9955	0.9852	0.8375	-0.0533	-0.1845	**-2.6534**
S4232	0.7705	0.5898	0.6872	-1.3159	**-2.3057**	**-3.1987**
S4233	1.0229	0.6603	0.7696	0.5001	**-1.9236**	**-2.1726**
S4234	0.9939	0.8752	0.7165	-0.0644	-0.8257	**-3.1879**
S4236	0.9254	0.5083	0.7135	-1.2106	**-2.1356**	**-2.4495**
S4237	0.9741	0.5105	0.8069	-0.4965	**-3.0054**	**-2.2168**
S4238	0.9501	0.5359	0.8899	-1.5079	**-3.9254**	**-1.6519**
S4243	0.8281	0.8683	0.7958	**-3.1611**	**-2.1536**	**-3.7101**
S4246	0.9155	0.9113	0.7569	-0.8930	-0.6862	**-2.0072**
S4248	1.1624	1.1330	0.9944	1.3799	1.1186	-0.0628
			EXCLUDED ITEMS			
S4235	0.7092	0.3938	0.7864	**-2.7466**	**-2.2125**	-1.2314
S4239	1.1098	1.0980	0.9414	1.0866	0.9894	-1.1125
S424	1.0400	1.0975	0.8649	0.4295	0.7317	-1.4318
S4241	0.9308	0.9191	0.9309	-1.6263	**-1.7246**	-1.2911
S4242	0.9515	1.2098	0.9567	-0.3226	1.3356	-0.3095
S4244	1.0028	1.0002	1.0733	0.0512	0.0045	0.8859
S4245	0.9014	1.0395	0.9966	**-2.0853**	1.0743	-0.0731
S4247	1.0315	1.0999	1.0652	0.4381	1.0973	0.5078
S4249	0.9623	0.9642	0.9044	-0.4714	-0.4526	-0.9805

In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are: ARIMA(p,1,q), ARIMA(0,1,1) and ARIMA(0,2,2). A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Table 4: US inventories results – Six-steps-ahead forecasts – ARIMA benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	MSFE ratio RC-ARIMA(1,1,2) vs ARIMA(0,2,2)	DM Test RC-ARIMA(1,1,2) vs ARIMA(p,1,q)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,1,1)	DM Test RC-ARIMA(1,1,2) vs ARIMA(0,2,2)
S42	1.4934	0.5955	0.7313	**2.1907**	**-1.7334**	**-2.5586**
S423	0.7791	0.4279	0.6828	-1.2402	**-2.7268**	**-2.3399**
S4231	1.0471	1.0424	0.8088	0.5332	0.4820	**-2.6183**
S4232	0.8175	0.7254	0.5647	-0.9709	-1.3304	**-4.1089**
S4233	1.0645	0.7748	0.6163	1.0473	-1.2510	**-2.4495**
S4234	1.0809	1.0039	0.5936	0.5313	0.0199	**-3.7380**
S4236	0.9458	0.5960	0.5146	-0.6398	-1.6175	**-3.0259**
S4237	0.9934	0.6032	0.7173	-0.0956	**-2.1144**	**-2.9908**
S4238	0.9630	0.6854	0.8509	-1.2825	**-2.6667**	**-2.0103**
S4243	0.8865	0.9203	0.8102	**-2.4080**	-1.4419	**-3.0412**
S4246	1.1424	1.0714	0.7205	1.3502	0.5823	**-2.1223**
S4248	1.2644	1.2412	1.0543	**1.8184**	**1.6652**	0.5619
			EXCLUDED ITEMS			
S4235	0.5702	0.5477	0.5249	**-2.5251**	-1.5291	**-2.3858**
S4239	1.1764	1.1586	0.9406	**1.9357**	**1.7498**	-1.1693
S424	1.0636	1.1207	0.7293	0.6225	0.8615	**-2.9070**
S4241	0.9372	0.9215	0.9121	-0.7406	-0.8551	-1.0101
S4242	1.5525	1.5999	1.1054	**2.4270**	**2.2479**	0.6357
S4244	1.0604	1.0607	1.2226	0.9283	0.9190	**1.7022**
S4245	0.9609	1.0253	0.9359	-1.0868	0.8284	-1.1523
S4247	1.1440	1.1511	1.0673	**2.5894**	**2.0848**	0.4682
S4249	0.9748	0.9729	0.8389	-0.3697	-0.3965	**-1.8126**

In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are: ARIMA(p,1,q), ARIMA(0,1,1) and ARIMA(0,2,2). A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Table 5: US inventories results – One-step-ahead forecasts – Exponential Smoothing (ETS) benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,N,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,N,N)
S42	0.4995	0.9224	0.4723	**-2.7188**	-1.1135	**-3.5305**
S423	0.2805	0.8760	0.2798	**-3.3297**	**-2.0800**	**-4.3943**
S4231	1.0132	0.9300	1.0351	0.1811	-1.1725	0.4002
S4232	0.6506	0.8310	0.7007	**-2.4817**	**-3.7680**	**-2.3724**
S4233	0.5111	0.8329	0.5092	**-2.8346**	**-2.0237**	**-3.3488**
S4234	0.8804	0.8920	0.8362	-1.1335	-1.4516	**-1.7585**
S4236	0.5394	0.9109	0.5639	**-2.3018**	-1.0704	**-2.4687**
S4237	0.6001	0.8901	0.6016	**-2.9022**	**-2.1430**	**-3.6374**
S4238	0.5391	0.9149	0.4875	**-4.0193**	-1.4193	**-4.4761**
S4243	0.8465	0.8161	0.8497	**-2.2833**	**-3.0451**	**-1.9433**
S4246	0.9092	0.8510	0.8981	-1.0487	**-1.9561**	-1.2295
S4248	1.0443	0.9844	1.0424	0.4817	-0.4953	0.3896
			EXCLUDED ITEMS			
S4235	0.4403	0.4594	0.4592	**-2.2651**	**-2.0206**	**-2.3807**
S4239	1.0695	1.0274	1.0737	1.3302	0.6713	**1.7737**
S424	1.0320	0.9927	0.9690	0.2316	-0.0548	-0.2353
S4241	0.9701	0.9380	0.9814	-0.9077	-1.3333	-0.7288
S4242	0.8671	1.0296	0.8807	-1.6398	0.4174	**-1.7192**
S4244	1.0080	1.0211	0.9494	0.1990	0.6009	-0.9604
S4245	1.0902	1.0902	1.0902	0.9908	0.9908	1.0030
S4247	1.1889	1.1785	1.1646	**1.7065**	1.6106	1.5713
S4249	0.9240	0.9086	0.9329	-1.0438	-1.2825	-0.9125

In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are in the Exponential Smoothing single source of error (ETS) family: The triplet (E,T,S) refers to the three components: error, trend and seasonality; thus, for instance, the model ETS(A,A,N) has additive errors, additive trend and no seasonality. A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Table 6: US inventories results – Three-steps-ahead forecasts – Exponential Smoothing (ETS) benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,N,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,N,N)
S42	0.4202	0.8243	0.3873	**-2.6093**	**-2.4417**	**-3.7653**
S423	0.2857	0.8244	0.2802	**-3.2985**	**-2.2483**	**-4.7399**
S4231	0.9922	0.9066	1.0120	-0.0926	-1.1682	0.1227
S4232	0.5688	0.7145	0.6256	**-2.4065**	**-4.3704**	**-2.4678**
S4233	0.5915	0.7559	0.5807	**-2.1934**	**-2.4959**	**-2.8512**
S4234	0.8391	0.7337	0.7512	-1.0393	**-2.6709**	**-2.2285**
S4236	0.4368	0.6965	0.4588	**-2.2861**	**-2.9189**	**-2.6846**
S4237	0.4693	0.7782	0.4522	**-3.2178**	**-2.7040**	**-5.0564**
S4238	0.4811	0.8775	0.4263	**-4.3408**	**-1.8889**	**-4.9614**
S4243	0.8531	0.8239	0.8583	**-2.2952**	**-2.7321**	**-2.0658**
S4246	0.9168	0.7424	0.8745	-0.6573	**-2.2955**	-1.0721
S4248	1.2033	0.9588	1.0225	1.6199	-1.0128	0.1528
			EXCLUDED ITEMS			
S4235	0.3228	0.4063	0.3496	**-2.5445**	**-1.9361**	**-2.6145**
S4239	1.1119	1.0454	1.1125	1.0876	0.5610	1.4515
S424	1.0479	0.9045	0.9127	0.3087	-0.8431	-0.5849
S4241	0.9294	0.9126	0.9801	-1.6143	**-1.7437**	-1.3077
S4242	1.0940	1.0669	0.9973	0.6860	0.5389	-0.0826
S4244	1.0009	1.0305	0.8478	0.0161	0.6563	**-2.2798**
S4245	1.0330	1.0330	1.0330	0.4887	0.4887	0.5057
S4247	1.1056	1.0787	1.0542	1.0726	0.7879	0.6613
S4249	0.9317	0.9092	0.9363	-0.8234	-1.1593	-0.6876

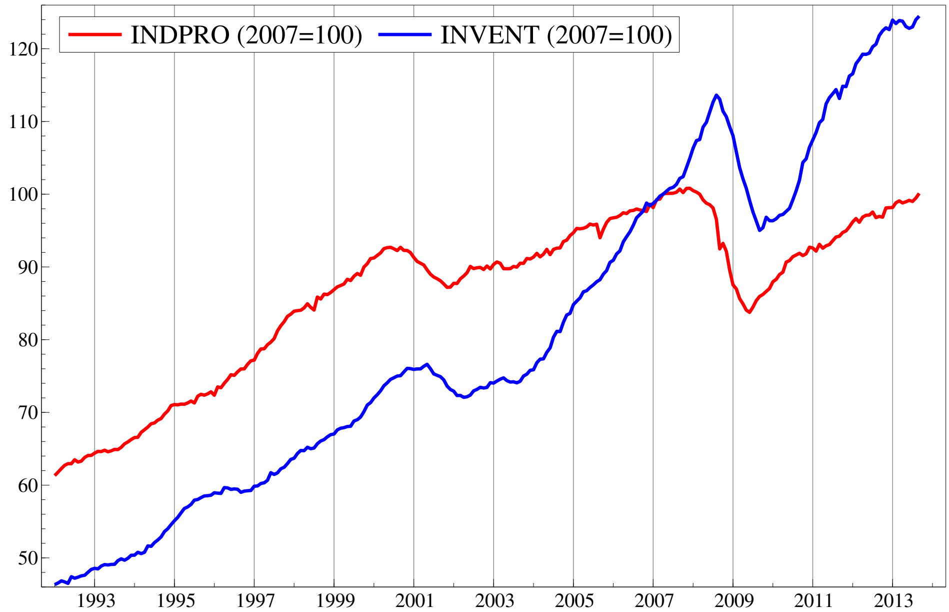
In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are in the Exponential Smoothing single source of error (ETS) family: The triplet (E,T,S) refers to the three components: error, trend and seasonality; thus, for instance, the model ETS(A,A,N) has additive errors, additive trend and no seasonality. A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Table 7: US inventories results – Six-steps-ahead forecasts – Exponential Smoothing (ETS) benchmarks

NAICS Code	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,A,N)	MSFE ratio RC-ARIMA(1,1,2) vs ETS(A,N,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A_d,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,A,N)	DM Test RC-ARIMA(1,1,2) vs ETS(A,N,N)
S42	0.5312	0.7206	0.4617	**-2.0250**	**-3.0398**	**-3.3875**
S423	0.3779	0.6942	0.3517	**-2.9014**	**-2.3537**	**-4.7372**
S4231	1.0422	0.9021	1.0324	0.4717	-1.0817	0.2845
S4232	0.7086	0.6029	0.7765	-1.4136	**-4.5974**	-1.3393
S4233	0.7283	0.6407	0.6765	-1.4544	**-2.4428**	**-2.4699**
S4234	0.9830	0.6214	0.7912	-0.0851	**-2.9978**	-1.5750
S4236	0.5413	0.4975	0.5520	**-1.7621**	**-3.6257**	**-2.3316**
S4237	0.5716	0.7067	0.5342	**-2.2811**	**-3.3832**	**-4.1587**
S4238	0.6489	0.8560	0.5677	**-2.9529**	**-2.0332**	**-3.5481**
S4243	0.9105	0.8738	0.9165	-1.6142	**-2.0034**	**-1.7403**
S4246	1.0715	0.7332	0.9080	0.5910	**-1.9753**	-0.8913
S4248	1.2970	0.9296	1.0147	**1.9880**	-1.2973	0.0847
			EXCLUDED ITEMS			
S4235	0.4355	0.3813	0.5205	**-2.1297**	**-2.6863**	**-1.7948**
S4239	1.1756	1.1327	1.1078	**1.8892**	1.5645	1.5754
S424	1.0990	0.7942	0.8997	0.6369	-1.9352	-0.6543
S4241	0.9295	0.9054	0.9932	-0.8091	-1.0014	-0.3175
S4242	1.5683	1.2618	1.0108	**2.3374**	**1.6601**	0.3830
S4244	1.0571	1.0766	0.8085	0.8703	1.2577	**-3.3891**
S4245	1.0380	1.0380	1.0477	0.8040	0.8040	1.1156
S4247	1.1649	1.1257	1.0434	**2.1301**	1.5694	0.7967
S4249	0.9545	0.9260	0.9895	-0.6656	-1.2294	-0.1325

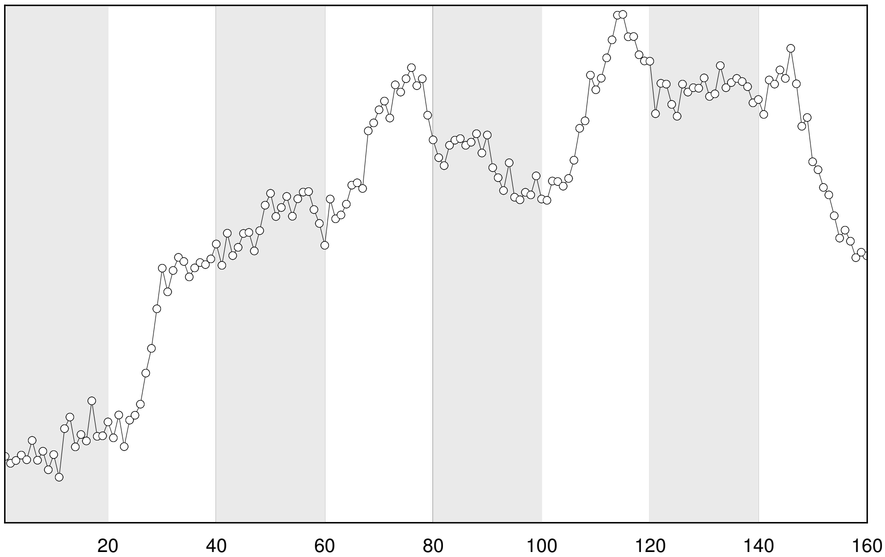
In-sample estimation period: 1992:01-2008:12. Out-of-sample forecasting period: 2009:01-2013:07. The benchmark models are in the Exponential Smoothing single source of error (ETS) family: The triplet (E,T,S) refers to the three components: error, trend and seasonality; thus, for instance, the model ETS(A,A,N) has additive errors, additive trend and no seasonality. A DM test with associated p-value smaller than 0.05 is shown in bold, implying a rejection of the null hypothesis (equal forecasting accuracy) at 5 percent level. Negative (positive) values of the DM test indicate that the RC-ARIMA(1,1,2) performs better (worse) than the alternative model. The excluded items are those not fulfilling conditions in Remark 3.

Figure B.1: Industrial Production Index and Merchant Wholesalers Inventories for the US



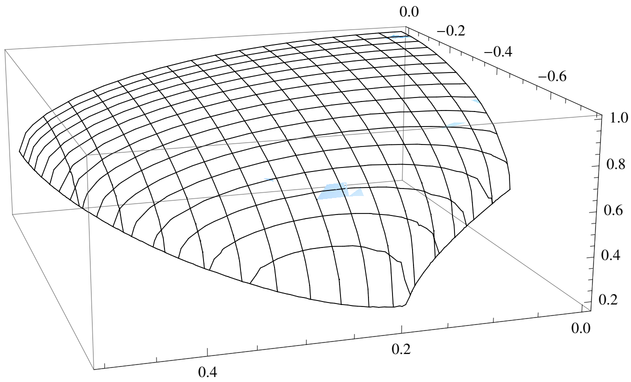
This graph shows the Industrial Production Index (INDPRO), Index 2007=100, Monthly, Seasonally Adjusted; Merchant Wholesalers Inventories (WHLSLRIMSA), Index 2007=100, Monthly, Seasonally Adjusted. Sample: 1992:01-2013:09. Source: Federal Reserve Bank of St. Louis.

Figure B.2: Simulated time series with switching dynamic behavior



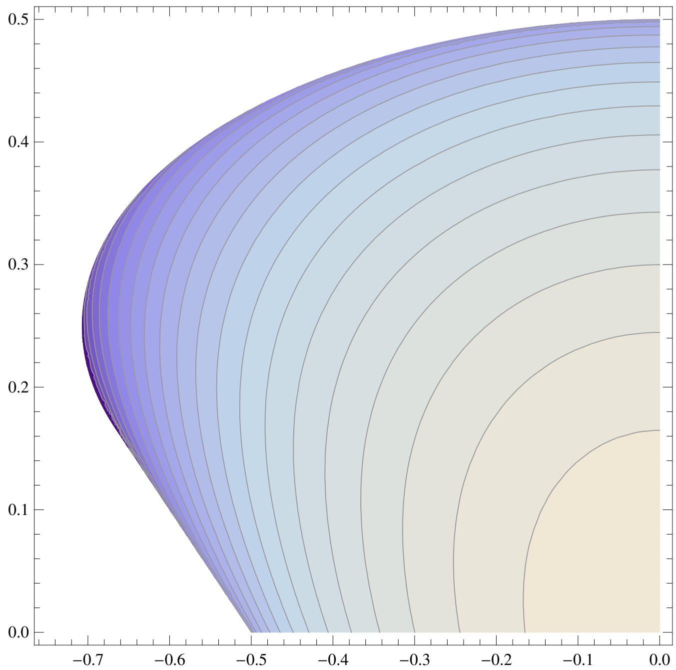
The above chart shows a simulated model as in (1) and (2). In the shaded areas the series behaves as a simple exponential smoothing dynamics, while in the non-shaded area the series behaves as a local linear trend.

Figure B.3: Variance (σ_a^2)



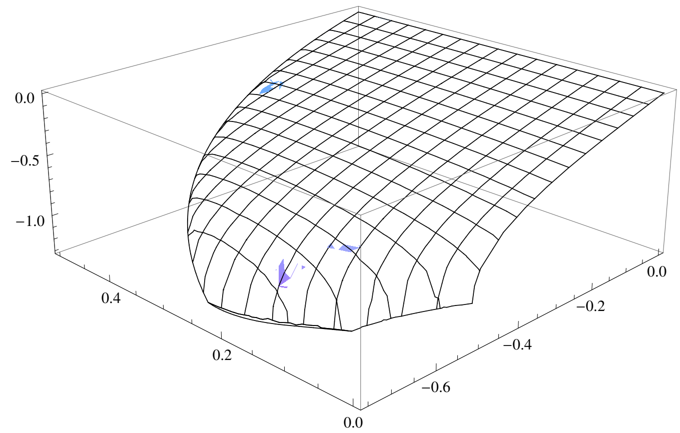
The above chart shows the variance (vertical axis) as a function of γ_1 and γ_2 having fixed $\gamma_0 = 1$.

Figure B.4: Variance (σ_a^2)



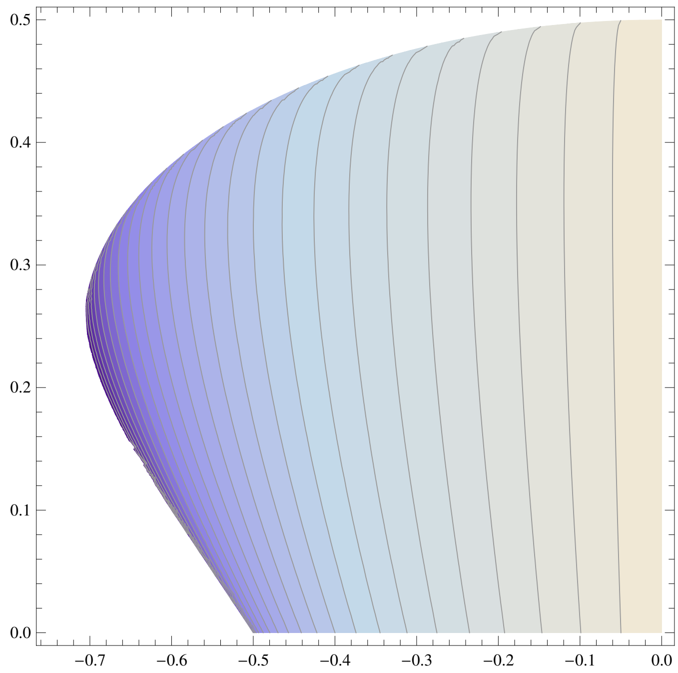
The above chart shows the contour plot of the variance by changing γ_1 and γ_2.

Figure B.5: θ_1



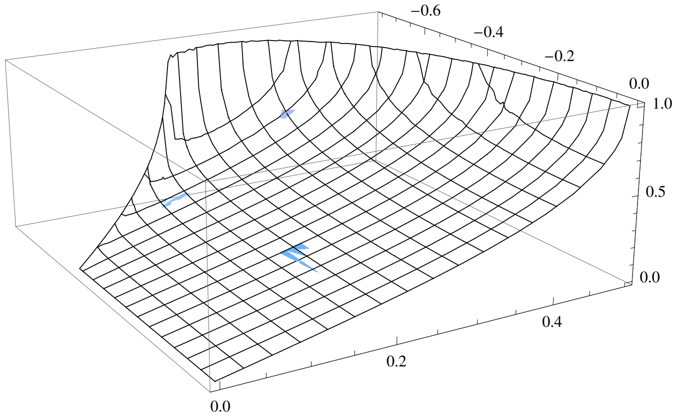
The above chart shows θ_1 as a function of γ_1 and γ_2, having fixed $\gamma_0 = 1$.

Figure B.6: θ_1



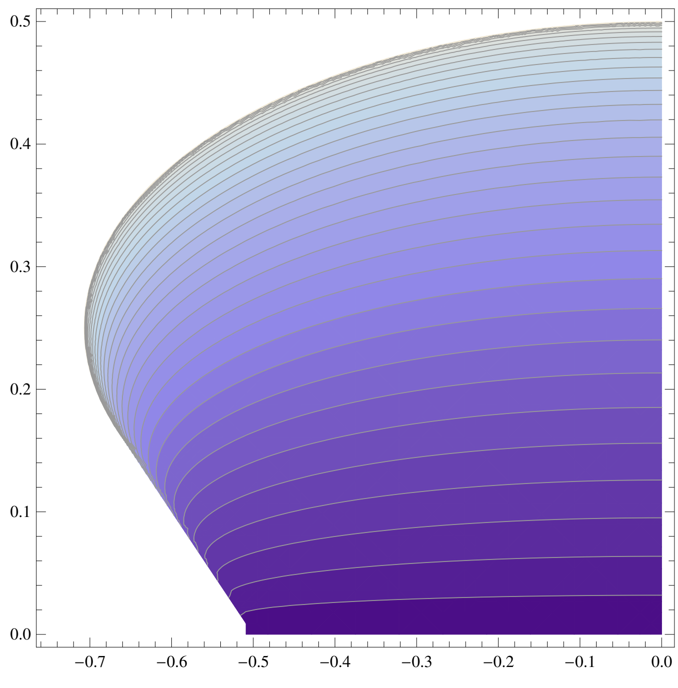
The above chart shows the contour plot of θ_1 as a function of γ_1 and γ_2, having fixed $\gamma_0 = 1$.

Figure B.7: θ_2



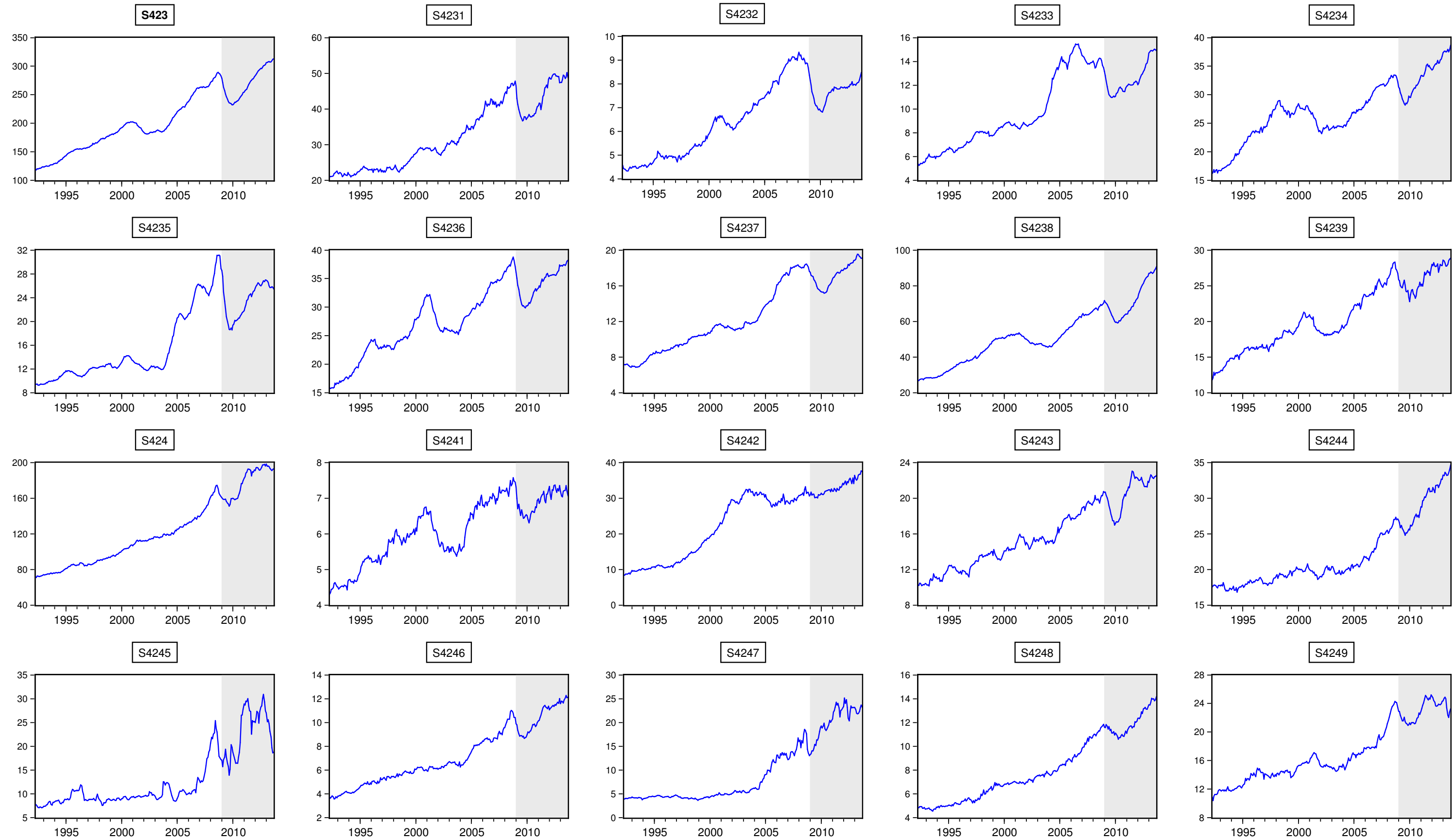
The above chart shows θ_2 as a function of γ_1 and γ_2, having fixed $\gamma_0 = 1$.

Figure B.8: θ_2



The above chart shows the contour plot of θ_2 as a function of γ_1 and γ_2, having fixed $\gamma_0 = 1$.

Figure B.9: US inventories: time series plots



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