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Is There Seasonality in Pakistan's Merchandise Exports and Imports? The Univariate Modelling Approach

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This paper investigates the existence of seasonal patterns in the quarterly merchandise export and import data of Pakistan from 1982:1 to 2002:1. Unit root tests are applied to determine whether the seasonal component in each variable exhibits stochastic non-stationarity. Deterministic and stochastic effects are isolated and quantified. Few alternate DGP specifications are identified, fitted and tested for their out-of-sample forecasting performance. A tentative finding is that deterministic effects are relatively more important than stochastic ones. However, integrated models, i.e., ARIMA, mixed ARIMA, and ARIMA-GARCH, outperform deterministic models with respect to forecasting.

1. INTRODUCTION

Pakistan's merchandise international trade is casually observed to follow a seasonal pattern. Exports are believed to regularly spike in certain quarters of the calendar year due to year-end shopping season in western countries, the destination of nearly two-thirds of our semi-manufactured and manufactured exports. Correspondingly, until quasi-autarky was attained in wheat production in mid-1990s, wheat imports were bunched in the last quarter of each calendar year.

While the writer is not aware of recent attempts at univariate modelling of Pakistan's quarterly macro-economic time series, two dated published papers by Mahmud and Nishat (1987) and Shaikh and Zaman (1983) employed univariate techniques of ARIMA to forecast annual rice exports from Pakistan. Univariate modelling, though second best to casual methods of forecasting, is appealing because of its modest demands on the amount of exogenous information as well as its timeliness. It is also useful in unveiling and distinguishing between deterministic and stochastic short-term seasonal patterns in the macro time series, which can later

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be subjected to more robust cointegration analysis. In a period of transition from forecasting based on annual economy-wide macro models to quarterly macro models, univariate models provide a convenient intermediate tool for planners and policy-makers in Pakistan for short-term forecasting of macro time series.

The purpose of this paper is to model and investigate quarterly series of Pakistan's merchandise exports and imports from 1982:1 to 2002:1 to observe any regular or stochastic seasonal trends. Few alternate data-generating processes (DGP) are identified and fitted to the data to generate acceptable out-of-sample forecasts for 5 quarters during 2001:1 and 2002:1. The paper is divided as follows. Deterministic and stochastic seasonality is modelled under a general regression framework in Section 2. The contribution of deterministic seasonality is isolated in Section 3. Estimates of alternate modelling of the two underlying data-generating processes are presented in Section 4. Section 5 outlines the out-of-sample forecasting performance of the various univariate models. Concluding remarks in Section 6 complete the paper.

2. GENERAL REGRESSION FRAMEWORK

(a) Quarterly Export of Goods

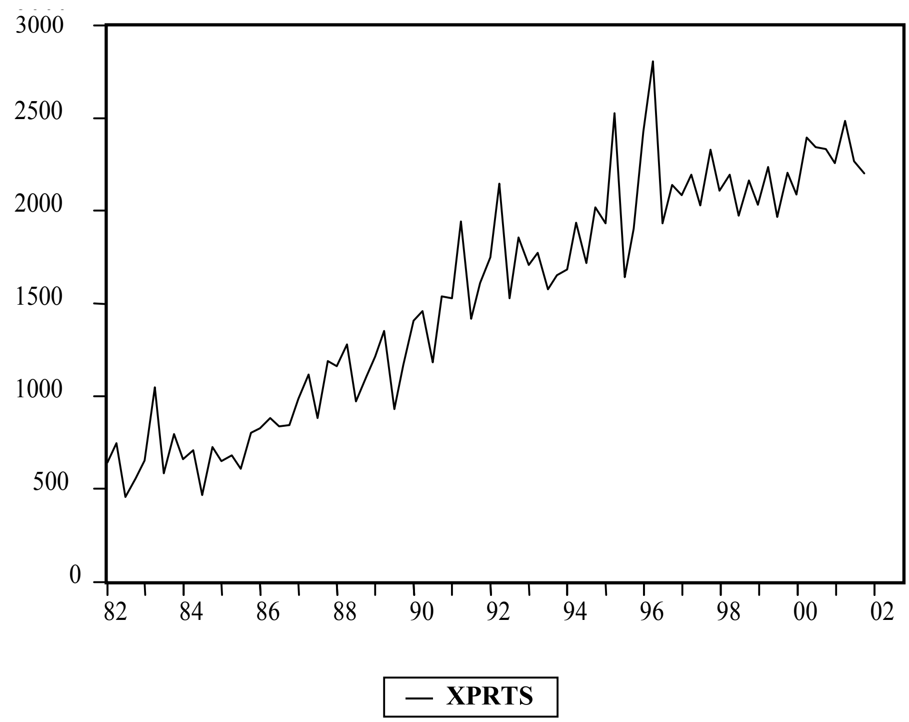
A look at the quarterly (unadjusted) exports (XPRTS, (X_t)) from 1982:q1 to 2001:q4 in billion US $ plotted in Figure 1 motivates the formulation of a specification for modelling and forecasting of the quarterly exports in subsequent sections of this paper. We observe that the series exhibits a rising trend with fluctuations around that trend; apparent volatility increasing during 91-93 and then again in the 1995–1997 period.[1]

Seasonal variations in exports can be one explanation for these fluctuations. Exogenous/supply shocks or speculative behaviour of exporters in response to volatility in exchange rates can also give rise to the observed variability across quarters. Seasonal fluctuations can be regular or deterministic, while the latter type are stochastic or non-stationary. Thus depending on the underlying nature of these fluctuations, the implications vary for model selection.

In order to identify the nature of these fluctuations we statistically test for the presence of seasonality within a very general regression framework that embodies the testing of deterministic and stochastic (unit roots/non-stationary) seasonality. The framework that tests for unit roots in the regular and in the seasonal polynomials is owed to Hylleberg, Engle, Granger, and Yoo (1990), and is usually referred to as HEGY. It consists of fitting the following equation to the unadjusted time series:

[1]However, empirically, the coefficient of variations (a crude measure of volatility) calculated for subgroups of 12 quarters each does not reveal exceptional volatility during these periods.

Fig. 1.



$$\Delta_4 X_t = \mu_t + \gamma_1 X_{1t-1} + \gamma_2 X_{2t-1} + \gamma_3 X_{3t-2} + \gamma_4 X_{3t-1} + \sum_{j=1}^{p} \varphi_j \Delta_4 X_{t-j} + \varepsilon_t$$

where

$$X_{1t} = (1 + L + L^2 + L^3) X_t$$
$$X_{2t} = -(1 - L + L^2 - L^3) X_t$$
$$X_{3t} = -(1 - L^2) X_t$$
$$\mu_t = \delta t + D1 + D2 + D3 + D4$$

and, μ_t contains the deterministic components, i.e., constant, trend, and seasonal dummies. The relevant null hypothesis for the seasonally unadjusted data is:

$\gamma_1 = 0$: unit root at the zero frequency;

$\gamma_2 = 0$: unit root at the biannual frequency;

$\gamma_3 = \gamma_4 = 0$: unit root at the quarterly frequency.

The maximum lag p=4 for the $\sum_{j=1}^{p}\varphi_j\Delta_4 X_{t-j}$ term was set by maximising $\overline{R}^2$. The estimated model, with 't' and τ statistics in parenthesis, is:

$$\begin{array}{lllllll} \Delta_4 X_t = 10.244t + & 209.168D1 + & 372.776D2 - & 21.549D3 + & 205.265D4 - & 0.098X_{1t-1} \\ (2.30) & (2.11) & (3.74) & (-0.22) & (2.15) & (-2.38) \\ 5\%cv & & & & & -3.53 \end{array}$$

$$\begin{array}{llllll} & -0.285X_{2t-1} & -0.557X_{3t-2} & -0.096X_{3t-1} + \sum_{j=1}^{p}\varphi_j\Delta_4 X_{t-j} & & \\ & (-2.32) & (-4.54) & (-0.79) & & \\ 5\%cv & -2.94 & -3.48 & -2.32/+2.28 \quad \ldots & \ldots \quad \ldots & (1) \end{array}$$

5 percent critical values (cv) given beneath t/τ statistics are from HEGY (1990) Tables 1A and 1B.[2] The null hypothesis $\gamma_1 = 0$ is not rejected with a test statistic of 2.385, which is less, in absolute value than the 5 percent critical value of 3.53. Similarly, the null hypothesis of $\gamma_2 = 0$ is not rejected with a test statistic of 2.323. On this basis the hypothesis of one unit root at the zero frequency and one at the biannual frequency is not rejected. Testing the joint null hypotheses $\gamma_3 \cap \gamma_4 = 0$ will indicate the existence of unit root at the quarterly frequency. The sample test statistic is 10.98, which is *greater* than the 5 percent critical value of 6.60, thus indicating a rejection of seasonal unit root or non-stationarity. However, the result is not so unambiguous. The null hypothesis of $\gamma_4 = 0$ is not rejected while that of $\gamma_3 = 0$ is rejected. A tentative conclusion is that the data supports unit roots at the long-run and zero frequencies, but do not establish non-stationarity at the seasonal frequencies unambiguously.

The above sample values of the test statistics for various frequencies do not unequivocally support *either* the null hypothesis that the series is seasonally integrated, (I(0,1)) *or* the alternative hypothesis that the series is I(1,0) or I(0,0).[3] The above test is also invariant to the drift parameter and starting values of γ_0 when testing the I(1) hypothesis with a non-constant drift term (but no deterministic trend). Thus there is a need to conduct a joint test of the hypotheses $\gamma_1 = \delta = 0$. Rejection of this suggests acceptance of trend stationarity. The sample value of the test statistic is 2.86 as against the 5 percent critical value of 6.33. The null hypothesis of trend stationarity is therefore rejected.

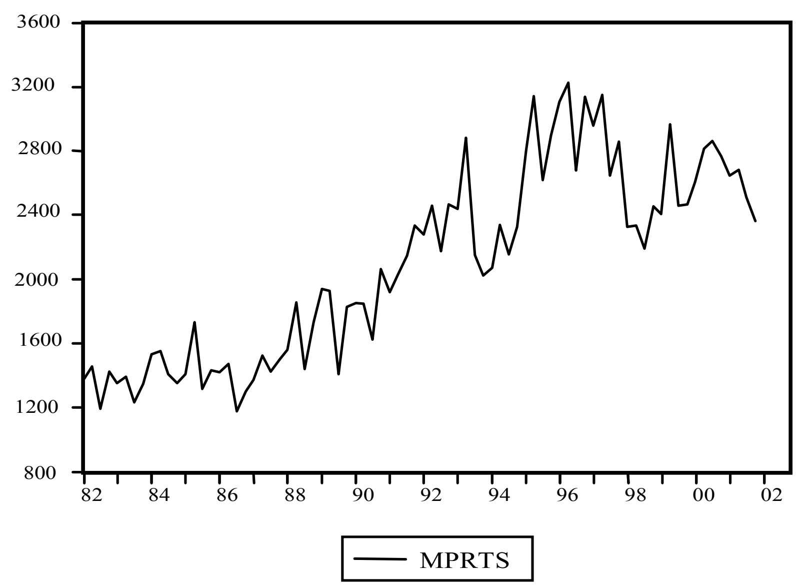
[2]Throughout the paper, critical values are marginal significance level.

[3]In variables being classified I(1,1), the first argument refers to the level of non-seasonal, or one-period, differencing while the second refers to the level of seasonal differencing required to render the variable stationary.

(b) Quarterly Import of Goods

Figure 2 plots the quarterly (unadjusted) imports (MPRTS, (M_t)) from 1982:q1 to 2001:q4. In a period of eleven years, i.e., from 1982 to 1992, the quarterly imports more than doubled from US $ 1.2 billion to 2.9 billion, moving along a steep rising trend with periodic mild fluctuations. Since early 1993, the pre-1992 rising quarterly trend is replaced by apparent constancy generated by wide quarterly fluctuations in merchandise imports ranging from US $ 2.0 to 3.2 billion per quarter. This suggests the possibility of a structural break due to the following reasons: liberalisation of current account, frequently adjustable (crawling) exchange rate peg since 1992, dwindling reserves, and speculative import behaviour of traders. Lumpy imports due to motorway construction, building of PARCO refinery, and the yellow taxi cab scheme may have generated wide quarterly fluctuations. One can also interpret this bandwidth as the "plateau" or levelling of imports after 30 years of import substitution and autarky in food production.

Fig. 2.



Therefore, before we test for seasonal unit roots, we need to test for the structural break in the data set. Thus, according to Patterson (2000), "if the structural break(s) is(are) not taken into account the unit root test leads to false non-rejection of the null of non-stationarity. Thus too often series are concluded to be non-stationary". In testing for structural break, I test two alternate specifications that are an extension of the standard Dickey-Fuller unit root tests: (a) relying on visual inspection I regard the post-1993:2 exchange rate liberalisation period as instrumental to the structural shift in the behaviour of imports. Thus the Perron (1989) approach is applied to a known single structural break; (b) the Zivot and Andrews (1992) data-based framework is employed to identify the "unknown" breakpoint yields post-1997:1 as a structural shift. Both the results with and without seasonal dummies are reported as Appendix A. The values of the test statistic [generated by Zivot and Andrews (1992)] lead to the acceptance of null hypothesis, i.e., the series is non-stationary.[4] These results provide support to the premises that the underlying DGP process of either the deterministic or the stochastic seasonality in imports is not sensitive to the apparent swings observed in the post-1993:2 period.

The estimated results obtained from applying the HEGY test, including the dummy for structural break (*D97)* on import series, is as follows:

$$\begin{array}{lllllll}
\Delta_4 M_t = 17.022t & +\,510.79D1 & +\,733.864D2 & +\,252.113D3 & +\,489.71D4 & -\,0.137M_{1t-1} \\
\quad (3.64) & (3.41) & (4.87) & (1.68) & (3.33) & (-3.81) \\
5\%cv & & & & & -3.53
\end{array}$$

$$\begin{array}{llllll}
 & -\,0.371M_{2t-1} & -\,0.714M_{3t-2} & -\,0.042M_{3t-1} & +\sum_{j=1}^{p}\varphi_j \Delta_4 M_{t-j} & -\,22.348D97 \\
 & (-2.82) & (-5.25) & (-0.32) & & (3.06) \\
5\%cv & -2.94 & -3.48 & -2.32/+2.28 & \ldots & \ldots
\end{array} \qquad (2)$$

The results are remarkably similar to the ones obtained for exports, except that the null hypothesis of unit root at zero frequency is rejected on the basis of 5 percent critical value, while at long-run frequency it is close to rejection, i.e., test statistic of 2.824 as against 5 percent critical value of 2.94. The data do not support unit roots at zero frequency, but do not establish non-stationarity at the seasonal frequencies unambiguously. Testing of trend stationarity, i.e., $\gamma_1 = \delta = 0$ yields the test statistic value of 5.17 against the 5 percent critical value of 6.33, suggesting the absence of trend stationarity.

3. THE IMPORTANCE OF DETERMINISTIC SEASONALITY

(a) Exports

The above results favour the presence of one-period non-stationarity, and deterministic as opposed to stochastic seasonality, although the presence of the latter cannot be conclusively rejected. In this section we empirically test the specification suggested by OCSB (1990) to assess the importance of stochastic and deterministic seasonality separately. The general dynamic equation and its empirical estimates are as follows:

[4]The Frances and Haldrup (1994) procedure for incorporating multiple additive outliers was also tested. The results not reported in the paper indicated the acceptance of the null hypothesis.

$$X_t^* = \alpha_0 + \alpha_1(D_{1t} - D_{4t}) + \alpha_2(D_{2t} - D_{4t}) + \alpha_3(D_{3t} - D_{4t})$$
$$\phi_1 X_{t-1}^* + \phi_2 X_{t-2}^* + \phi_3 X_{t-4}^* + \phi_4 X_{t-8}^* + \phi_5 X_{t-12}^* + \mu_t$$

$$\underset{(22.50)}{X_t^* = 46.559} - \underset{(61.65)}{45.455}(D_{1t} - D_{4t}) + \underset{(57.76)}{245.35}(D_{2t} - D_{4t}) - \underset{(90.50)}{287.079}(D_{3t} - D_{4t})$$
$$- \underset{(0.12)}{0.419 X_{t-1}^*} - \underset{(0.13)}{0.335 X_{t-2}^*} + \underset{(0.13)}{0.161 X_{t-4}^*} - \underset{(0.12)}{0.167 X_{t-8}^*} + \underset{(0.12)}{0.017 X_{t-12}^*} \quad \ldots \qquad (3)$$

Where

D_{it} = seasonal dummies for I=1, 2, 3,4

X_t^* = first-order non-seasonal difference of exports.

std.errors in parenthesis.

The selection of the above seasonal lags for export series leaves the residuals free from autocorrelation. Table 1A summarises the results in terms of the importance of deterministic and stochastic seasonality. It also reports the probability (p) value for testing the null hypothesis that either $\alpha_1 = \alpha_2 = \alpha_3 = 0$ (no deterministic seasonality) or $\phi_3 = \phi_4 = \phi_5 = 0$ (no stochastic seasonality). The marginal R^2 is computed as

1-URSS/RRSS,

where URSS is the residual sum of squares from (3) while RRSS is the residual sum of squares for each of the two restricted equations, i.e., one without seasonal dummies and the other without seasonal lags. Marginal R^2 values are comparable as each restricted specification is characterised by an equal number of parameters. Under the conventional 5 percent level, the above p-values suggest that seasonal dummies are effective in capturing the seasonality in quarterly exports. Excluding seasonal lags, the above specification also yields the percentage seasonal patterns in the detrended series of exports. Table 1B reports the percentage by which each

Table 1A

Deterministic and Stochastic Seasonality in Detrended Series

Deterministic		Stochastic	
Marginal R^2	p-value	Marginal R^2	p-value
	Exports		
0.2640	0.0002	0.0492	0.4242
	Imports		
0.4109	0.0000	0.0768	0.2127

Table 1B

Percentage Seasonal Patterns in Detrended Series

Quarter					
1	2	3	4	SEE	R^2
		Exports			
–0.35	12.05	–22.96	11.26	176.60	0.5989
		Imports			
0.34	7.36	–14.82	7.12	192.56	0.4853

series deviates from its overall mean in each of the four quarters of the year. The fourth quarter is determined by the restriction that $\Sigma\ \alpha_i = 0$ over the year. Nearly sixty percent of non-trend variation is explained by the seasonal dummy variables alone.

(b) Imports

The OCSB (1990) specification is also applied to the merchandise import data to assess the importance of stochastic and deterministic seasonality separately:

$$\begin{aligned} M_t^* &= \underset{(23.83)}{31.305} + \underset{(53.73)}{29.819}(D_{1t} - D_{4t}) + \underset{(65.35)}{324.651}(D_{2t} - D_{4t}) - \underset{(86.35)}{496.857}(D_{3t} - D_{4t}) \\ &\quad + \underset{(0.14)}{0.222}M_{t-7}^* - \underset{(0.14)}{0.341}M_{t-9}^* - \underset{(0.14)}{0.095}M_{t-4}^* - \underset{(0.13)}{0.186}M_{t-8}^* - \underset{(0.15)}{0.172}M_{t-12}^* \quad \ldots \end{aligned} \tag{4}$$

M_t^* = first-order non-seasonal difference of imports.
std.errors in parenthesis.

At 5 percent level, the p-values given in Table 1A imply that seasonal dummies successfully capture the seasonality in quarterly imports. Percentage seasonal patterns in the detrended series of imports given in Table 1B are from a simpler specification (excluding seasonal lags) of the above model. Fifty percent of non-trend variation is explained by the seasonal dummy variables alone.

4. COMPETING SPECIFICATIONS OF DGP

There is a possibility that the above search for seasonal unit roots in the data-generating process (DGP) remains inconclusive due to the low power of unit root tests itself. Enders (1995) states, “unit root tests do not have the power to distinguish between a unit root and a near unit root process…Moreover they have little power to distinguish between trend stationarity and drifting processes”. Haldrup and Hylleberg (1991) argue that “for practical purposes the question of whether a time series is integrated is not a question of whether the root is exactly one or strictly less than one, but rather whether the time series contains a strongly autocorrelated component that can justify the series to be *approximated* as an integrated process".

The alternative specifications modelled and estimated in this section are motivated by the suggestion of Patterson (2000): "Thus, it may be that for some purposes a 'nearly' integrated process should be treated as an integrated process. Similarly a unit root process may be 'nearly' stationary and it may be better for some purposes to treat it as a stationary process". One purpose of this exercise was not only to model the DGP of merchandise export and import series but also to assess its out-of-sample forecast against the actual performance, and thereby provide planners with a reliable specification to aid in generating consensus forecasts for the quarterly exports and imports. Consequently, the last 5 quarters, i.e., 2001:1 to 2002:1, of actual data were excluded from the estimation of Equations 3 and 4 in Section 3, and alternative specifications estimated in this section.[5]

(a) Exports

A one-period non-seasonal difference and a one-period seasonal difference, $(1-B)(1-B^4)$, applied to log of exports only helped to eliminate autocorrelation at the 12th and 24th lag, as the Ljung-Box Q-statistic value at 4th and 8th lag exceeded the critical χ^2 -value at 1 percent level. Applying a filter such as (1-B), and $(1-B)^2(1-B^4)$ separately to log exports yielded significant autocorrelations even at the 12th and 24th lag in terms of Q-statistic. Thus the log of export series used in the alternative specifications of DGP is I (1,1).

Appendix B contains the estimated results of the three alternative specifications selected for modelling the DGP of Pakistan quarterly exports. (1) A pure ARIMA (4,(1,1),3) structure that minimises the dynamic out-of-sample forecast, mean absolute percent forecast error (MAPE) was chosen after some experimentation. Few combinations of 'p' and 'q', although superior in terms of AIC and Schwartz Bayesian Criterion (SBC), performed poorly in terms of the MAPE. This particular approach for model selection can be termed as a crude forecast-based model selection. (2) We chose a multiplicative or mixed ARIMA model of order $(p,d,q)x(P,D,Q)_4$, where p and P are the order of non-seasonal and seasonal autoregressive terms, and q and Q are the non-seasonal and seasonal order of moving average terms respectively. The symbols d and D represent the order of non-seasonal and seasonal filters applied to achieve stationarity. The non-seasonal and seasonal lag structure combination $(3,1,4)x(4,1,4)_4$ of MxARIMA (1) was chosen on the basis of minimum SBC. (3) The non-seasonal and seasonal AR and MA combination $(1,1,4)x(3,1,4)_4$ of MxARIMA (2) is based on minimising dynamic out-of-sample forecast MAPE.

[5]However, the data for the period 2001:1 to 2001:4 are included in the unit root testing procedure.

The results in Appendix B indicate that the selected lag structures for the integrated models fit the export data reasonably well. Only the autoregressive term of order 3 in MxARIMA (1) is statistically not significant. Summary statistics of residuals generated from these estimations are given in Table 2. The Bartlett test was used to test the equality of variances of residuals across the 4 quarters. Various specifications successfully pass most of the tests for the absence of autocorrelations and heteroscedasticity in the residuals at the conventional 5 percent level of significance, except that the residuals from the export Equation 3 still exhibit ARCH tendencies of order 1.

Table 2

Summary Statistics for Alternative DGP Specifications

A. Exports

	Eqn. 3	ARIMA	MxARIMA (1)	MxARIMA (2)
Adj-R^2	0.6694	0.4897	0.6298	0.6175
LM-Test	4.94	6.08	1.68	2.95
Bartlett Test	3.10	1.36	2.15	1.40
ARCH-LM (1)	3.32	3.25	0.01	2.56
ARCH-LM (4)	14.82[1]	3.78	0.60	5.23
Q-Stat (4)	3.59	–	–	–
Q-Stat (8)	7.04	4.11	2.15	6.07
Q-Stat (12)	9.06	6.36	7.63	11.84
Q-Stat (24)	17.75	18.31	21.45	28.83

[1]Null hypothesis of no serial correlation at 5 percent marginal significance level is rejected.

B. Imports

	Eqn. 4	ARIMA
Adj-R^2	0.6141	0.4280
LM-Test	2.33	0.95
Bartlett Test	1.22	0.81
ARCH-LM (1)	0.18	0.03
ARCH-LM (4)	7.36	1.27
Q-Stat (4)	2.22	0.35
Q-Stat (8)	4.55	3.29
Q-Stat (12)	8.38	5.96
Q-Stat (24)	22.49	22.36

(b) Imports

In our search for alternate modelling of DGP of goods import, we estimate an ARIMA model whose autoregressive and moving average order of (6,(1,1),4) is determined by using the Breush-Godfrey LM test. As a by-product it also leads to fulfilling the AIC and SBC criteria. The estimation results from fitting an ARIMA specification are reported as Appendix B. All the autoregressive terms are statistically significant and exhibit a declining trend in their values. Except the fourth-order moving average term, the remaining three MA terms are significant at the 1 percent level.

Visual depiction of the quarterly imports behaviour in Figure 2 indicates considerable volatility, which may be due to importing behaviour motivated by the unstable exchange rate policy/foreign exchange reserves and other structural factors, as mentioned above. Thus volatility clustering as observed in post-1993 era violates the assumption of constant residual variance presumed in the standard ARIMA analysis. Formally subjecting the residuals from ARIMA specification to ARCH-LM tests (up to fourth-order) did not indicate the presence of ARCH effects (Table 2b). However, to assess the forecasting performance of a competing specification, the ARIMA-GARCH estimates under the ML method were obtained as follows. The ARCH-GARCH order was determined by adding to the variance equation the additional lagged squared residuals and lagged forecast variance as long as the log of the likelihood function increased significantly. Finally, some experimentation was conducted on whether the MA or the AR orders could be decreased. The latter is appropriate because, as Weiss (1984) point out, "ignoring ARCH will lead to identification of ARMA models that are overparameterised". This paper reports two specifications that had the highest and the second-highest value of the log of the likelihood function. The empirical estimate of the specification that outperforms in *ex-ante* forecasting is presented below, while the other with the highest value of the log of likelihood function is reported as Appendix C.

$$\begin{aligned}
\Delta_1\Delta_4 \log M_t &= \underset{(-1.40)}{-0.003} - \underset{(-1.46)}{0.175 M_{t-2}} + \hat{\varepsilon}_t - \underset{(-1.58)}{0.068\varepsilon_{t-1}} + \underset{(1.57)}{0.072\varepsilon_{t-3}} - \underset{(-34.55)}{0.910\varepsilon_{t-4}} \\
\hat{\sigma}_t^2 &= \underset{(2.26)}{0.005} - \underset{(-2.28)}{0.238\hat{\varepsilon}_{t-1}^2} - \underset{(-2.32)}{0.133\hat{\varepsilon}_{t-2}^2} - \underset{(-1.22)}{0.089\hat{\varepsilon}_{t-3}^2} + \underset{(5.307)}{0.704\hat{\sigma}_{t-1}^2} \qquad \ldots \qquad (5)
\end{aligned}$$

The ARIMA coefficients are significant between the 10-15 percent level, while except the third-order ARCH term, the remaining ARCH-GARCH terms are significant at the 1 percent level. However, note that although the sum of coefficients at 0.244 is less than one, the estimates of the α_i =1, 2, 3 are negative, and so the Bollerslev conditions for non-negativity are not met. However, as Nelson and Cao (1992) show in GARCH (1, q) models with q>1, the requirement that all the coefficients be non-negative can be relaxed.[6] The small value of the sum of coefficients indicates that the volatility shocks are relatively short-lived.

5. FORECASTING PERFORMANCE

(a) Exports

A comparison of actual values with out-of-sample forecasts, including summary statistics, i.e., RMSE and MAPE, both under the dynamic and static scenarios for the 5 quarters from 2001:1 to 2002:1, are given in Table 3.[7] The out-of-sample forecasting performance of various alternative modellings of DGP can be

Table 3

Forecast Performance: Exports

	Eqn.3	ARIMA	MxARIMA (1)	MxARIMA (2)
Dynamic Forecasts 2001:1–2002:1				
RMSE*	160.65	159.17	145.55	136.66
MAPE*	6.18	6.22	5.29	5.00
Actual				
2256	2352	2442	2242	2316
2486	2656	2663	2692	2618
2264	2315	2240	2178	2036
2200	2451	2388	2387	2244
2086	2529	2631	2282	2295
Static Forecasts 2001:1–2002:1				
RMSE*	117.86	130.22	152.13	209.94
MAPE*	4.79	4.83	5.79	6.69
Actual				
2256	2352	2392	2269	2155
2486	2600	2516	2680	2410
2264	2208	2052	2104	1865
2200	2374	2262	2372	2165
2086	2308	2420	2116	2130

*Based on published value of exports during four quarters, 2001:1 to 2001:4.

[6]Although the estimation results of the specification given in Appendix C are more robust, they fail to meet the Bollerslev conditions for non-negativity. However, the heteroscedastic consistent 't' statistics are consistent for all coefficients for both specifications.

[7]The actual values for 2001:1 to 2002:1 are taken from the IMF's Direction of Trade CD, March 2003.

summarised as follows. (a) No single specification unequivocally outperforms the others across the dynamic/static spectrum and/or across each of the four quarters. (b) Out-of-sample dynamic forecasts for four quarters of 2001 by the Mixed ARIMA specifications have a lower RMSE than the deterministic and pure ARIMA models. (c) Static simulation of deterministic and pure ARIMA specifications yields lower 2001 forecast errors (RMSE and MAPE) as compared to mixed the ARIMA models.[8] (d) The fifth quarter ahead dynamic forecasts are generally poor except for those generated by the Mixed ARIMA models.

(b) Imports

Comparing the three specifications in Table 4 of the out-of-sample forecasting performance of the import of goods, we note the following: (a) ARIMA-GARCH specification followed by the general dynamic specification embodied in Equation 4

Table 4

Forecast Performance: Imports

	Dynamic Forecasts 2001:1– 2002:1		
	Eqn.4	ARIMA	ARIMA-GARCH
RMSE*	362.86	449.10	163.52
MAPE*	12.46	16.07	4.74
Actual			
2648	2951	2884	2660
2682	3083	3251	2946
2510	2544	2704	2496
2362	2885	2987	2555
2473	2953	3009	2526
	Static Forecasts 2001:1– 2002:1		
RMSE*	344.54	298.16	203.02
MAPE*	12.60	11.57	7.05
Actual			
2648	2951	2994	2655
2682	2781	2885	2929
2510	2142	2214	2282
2362	2851	2690	2590
2473	2459	2323	2290

[8]Bias component of the pure ARIMA model was the lowest, and the variance component of the deterministic model was smaller than that of the other three models.

outperforms the integrated simple ARIMA specification in terms of RMSE and MAPE for the dynamic and static forecasts. The forecast summary statistics for ARIMA specification are marginally better than dynamic specification under static simulation. (b) In terms of absolute differences between the actual and the forecast values, the first and third quarter dynamic forecasts from ARIMA-GARCH specification are superior to the forecasts for the remaining quarters. Under static simulation, distance first quarter forecast is poorer than the immediate first quarter forecasts.

6. CONCLUDING REMARKS

The above empirical investigation does not conclusively establish the presence of seasonality in Pakistan's quarterly merchandise exports and imports. The lack of unambiguous evidence indicates that testing for seasonality in Pakistan's quarterly macro time series including exports and imports may require techniques of VAR, multivariate representation of seasonal time series [Flores and Novales (1997)], and univariate periodic error correction model (PECM) [Franses and Romijn (1993)]. At a more specific level, tentative findings of the present empirical investigation are: (a) Sixty percent of non-trend exports and nearly fifty percent of non-trend imports are explained by the seasonal dummy variables. Moreover, in terms of relative explanatory power, deterministic effects are more important than stochastic ones in both series. (b) In contrast to the higher explanatory power of the deterministic model, the out-of-sample forecasting performance of the general dynamic model in most cases is marginally poorer than that in the pure or mixed ARIMA or ARIMA-GARCH models. In case of exports, mixed ARIMA forecast errors are smaller than those of the former specification under dynamic simulation. Similarly, pure ARIMA outperforms the former under static simulation. (c) Due to observed volatility in imports, identification of forecast-error-minimising DGP within an ARIMA framework proved to be more challenging than in case of exports. The forecasting performance of ARIMA-GARCH specification for imports is notably superior to forecasts generated from the deterministic and the pure ARIMA models. (d) Broadly, the immediate ahead out-of-sample quarterly forecasts (in our case the first quarter of the calendar year) and the third quarter forecasts from the best performing specifications are closer to actual values for both the series. However, depending on the timeliness of the available data from the recent past and the required number of periods ahead forecast, all the above specifications singly or jointly can be used to produce a 'model-generated' consensus forecasts for the quarterly exports and imports of Pakistan.

Appendices

Appendix A

Unit Root Tests for Structural Break in Imports

Variables	Dependent Variable: ΔM_t Structural Break 1993:2		1997:1	
C	299.53	335.27	460.32	503.73
	(2.55)	(2.67)	(3.81)	(3.93)
M_{t-1}	–0.316	–0.353	–0.478	–0.522
	(–3.05)	(–3.21)	(–4.04)	(–4.19)
TREND	10.707	11.805	14.700	16.000
	(2.92)	(3.02)	(3.85)	(3.97)
DVT_t	–8.479	–9.234	–21.159	–23.043
	(–2.00)	(2.01)	(–3.18)	(–3.20)
ΔM_{t-1}	–0.052	–0.086	0.053	0.039
	(–0.386)	(–0.644)	(0.39)	(0.29)
ΔM_{t-2}	0.027	0.015	0.108	0.106
	(0.202)	(0.123)	(0.827)	(0.859)
ΔM_{t-3}	0.141	–0.043	0.204	0.021
	(1.09)	(–0.362)	(1.63)	(0.185)
ΔM_{t-4}	0.249	0.476	0.296	0.505
	(2.02)	(4.487)	(2.49)	(4.98)
$D_{1t}–D_{4t}$	1.461	–	–2.375	–
	(0.03)	–	(–0.04)	–
$D_{2t}–D_{4t}$	162.03	–	162.57	–
	(2.93)	–	(3.06)	–
$D_{3t}–D_{4t}$	–196.06	–	–181.16	–
	(–3.37)	–	(–3.22)	–

t-Statistics in brackets.
$DVT_t = 0$ if $t \leq T_b$, $DVT_t = t$ if $t > T_b$ where T_b is the timing of structural break.

Appendix B

Estimation Results of Alternative Specifications

		Exports			Imports
		ARIMA	MxARIMA (1)	MxARIMA (2)	ARIMA
		AR Coefficients			
Non-seasonal	Φ_1	0.268	–0.476	–0.633	–1.242
		(0.117)	(0.129)	(0.103)	(0.223)
	Φ_2	–0.558	–0.498	–	–1.175
		(0.119)	(0.137)		(0.254)
	Φ_3	0.488	0.092	–	–0.902
		(0.114)	(0.135)		(0.284)
	Φ_4	–0.283	–	–	–0.686
		(0.115)			(0.249)
	Φ_5	–	–	–	–0.571
					(0.195)
	Φ_6	–	–	–	–0.473
					(0.125)
Seasonal	Ψ_2	–	–	–0.542	–
				(0.091)	
	Ψ_3	–	–	0.454	–
				(0.099)	
	Ψ_4	–	–0.805	–	–
			(0.080)		
		MA Coefficients			
Non-seasonal	Θ_1	–0.884	–	–	1.319
		(0.055)			(0.247)
	Θ_2	0.844	–	–	1.279
		(0.024)			(0.223)
	Θ_3	–0.954	–	–	1.327
		(0.069)			(0.240)
	Θ_4	–	–0.962	–0.885	0.383
			(0.012)	(0.051)	(0.241)
Seasonal	λ_3	–	–	–0.509	–
				(0.114)	
	λ_4	–	0.970	–0.364	–
			(0.013)	(0.153)	

Std.errors in parenthesis.

Appendix C

Alternate ARIMA-GARCH Specification

$$\Delta_1\Delta_4 \log M_t = -0.001 - 0.186 M_{t-2} + \hat{\varepsilon}_t - 0.101\varepsilon_{t-1} + 0.094\varepsilon_{t-3} - 0.919\varepsilon_{t-4}$$
$$(-1.09) \quad (-1.90) \qquad\qquad (-3.01) \quad (2.37) \quad (-42.51)$$

$$\hat{\sigma}_t^2 = 0.002 - 0.222\hat{\varepsilon}_{t-1}^2 + 0.947\hat{\sigma}_{t-1}^2$$
$$(1.57) \quad (-3.17) \qquad (6.27)$$

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