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## Lahore School of Economics



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# One-Step-Ahead Forecastability of GARCH (1,1): A Comparative Analysis of USD- and PKR-Based Exchange Rate Volatilities

**Abdul Jalil Khan*** **and Parvez Azim****

**Abstract**

*This study aims to capture volatility patterns using GARCH (1,1) models. It evaluates these models to obtain one-step-ahead forecastabilities by employing four major forecasting evaluation criteria, and compares two different currencies—the Pakistan rupee and the US dollar—as domestic and foreign currency-valued exchange rates, respectively. The results show that using an international vehicle currency is favorable in Pakistan's context. However, the Kuwaiti dinar, Canadian dollar, US dollar, Singapore dollar, Hong Kong dollar, and Malaysian ringgit are found to be preferable when performing direct international transactions. Using the root mean square errors and mean absolute errors techniques, the study also assess the robustness of measuring one-step-ahead forecasts.*

**Keywords:** Time series analysis, GARCH models, foreign exchange markets, forecasting, exchange rate volatility, Pakistan.

**JEL classification:** C22, C53, F31, F37, F44.

## 1. Introduction

Exchange rate volatility became an important issue after the conversion of the exchange rate system from a fixed regime to a flexible one in the 1970s and onward. Many studies have tried to capture the patterns of volatile exchange rates. Since volatility was an important concern in stock markets, various methods were developed to control the effect of volatility. Consequently, when the issue of exchange rate volatility arose, the available literature on testing, estimating, and forecasting volatility allowed researchers to evaluate these techniques within the context of exchange rate fluctuations. This article applies recent volatility techniques to understand volatility patterns and assess the forecasting capacity of volatility models, using various exchange rates.

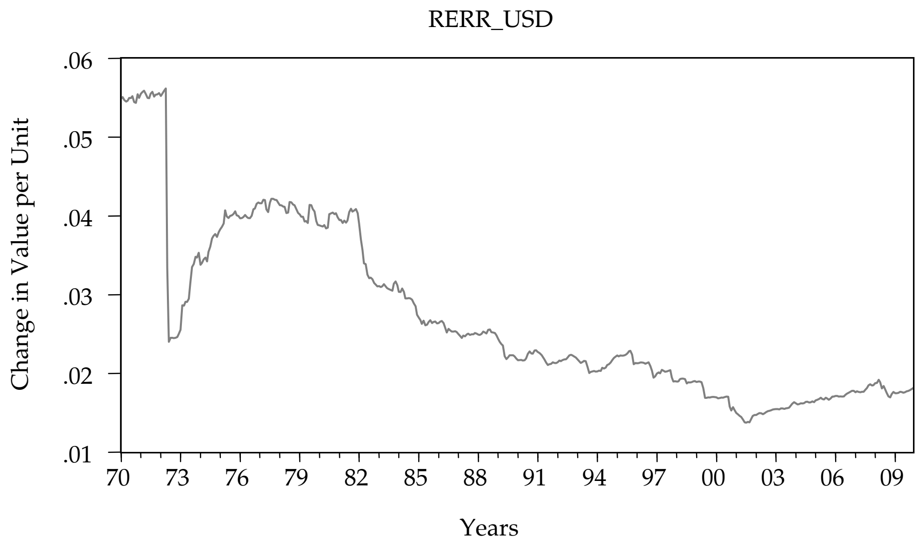
* PhD Scholar, Government College University, Lahore.
** Dean, Faculty of Arts and Social Sciences, Government College University, Faisalabad.

We focus on two different exchange rate bases in this study: (i) the Pakistan rupee (PKR) to measure direct or domestic currency-valued exchange rates because all Pakistan's significant trading partners are considered in choosing a sample; and (ii) the US dollar (USD) to calculate indirect or foreign currency-valued exchange rates because most world transactions in trade, capital movements, and financial dealings are made in US dollars. In addition, the US dollar is universally accepted, given that (i) the US has extensive trade links with the rest of the world, (ii) countries prefer to use it as a currency of foreign exchange reserves, and (iii) it has the capacity to be converted into gold after demonetization.

Most traders and investors involved in the exchange of goods and services internationally prefer to measure their costs and profits in USD terms. Historically, all developing countries have had close connections with the US either in the form of trade and investment or as aid, grants, or loans. This has allowed the countries of the world to agree to use US dollars as an acceptable international currency when making financial transactions with each other. Further, the demonetization of world currencies virtually bound developing countries to accumulate their foreign reserves mainly in US dollars.

However, this does not undermine the importance of local currencies because, as a vehicle currency, the US dollar can affect international transactions by raising risk and introducing volatility, and through recurrent speculative attacks. Moreover, US policies may have a variety of impacts on development in Pakistan. This has made it crucial for Pakistan to reconsider and revise its policies on international transactions and foreign reserve accumulation. Foreign exchange rates are the major player in this case because of the constant decline in the value of domestic currency (see Figure 1). International traders and investors need a stable exchange rate to make consistent future decisions and to keep the burden of international payments manageable.

**Figure 1: Monthly real exchange rate of PKR in terms of USD**




In recent research, exchange rate stability is assumed to be the most vital element to ensure the sustainable flow of trade, capital, and foreign reserves (see Esquivel & Larraín, 2002; Bahmani-Oskooee, 2002; Arize, Malindretos, & Kasibhatla, 2003; Crowley & Lee, 2003; Akyüz, 2009). We attempt to add to the literature on exchange rate volatility by using the generalized autoregressive conditional heteroskedasticity or GARCH (1,1) approach. We also explore its effective forecastabilities measured by four main loss functions: the root mean square error (RMSE), mean absolute percent error (MAPE), mean absolute error (MAE), and Theil's inequality coefficient (TIC).

It is useful to identify those currencies that can be used to finance trade and capital flows with more certainty by using GARCH (1,1) models as an effective volatility proxy. This allows policymakers to choose a better, more stable, currency (either a domestic or international vehicle currency) to finance trade, investment, and the accumulation of foreign exchange reserves. It helps minimize the risk involved in international transactions because of volatile exchange rates, especially when Pakistan engages in bilateral trade with its close trading partners.

This article is organized as follows. Section 2 explains the study's objectives and the hypothesis to be tested. Section 3 provides a brief literature review describing the empirical foundations of GARCH application. Section 4 describes the sample, data, and estimation procedure used to generate volatility variables. Our results are presented and analyzed in Section 5; and Section 6 gives the major empirical findings, policy implications, and conclusions.

## 2. Objectives and Hypothesis

The purpose of this study is to gauge the possibilities of using domestic currencies directly—to avoid the given level of risk involved in using a vehicle currency—in bilateral trade to conduct international financial transactions smoothly with reference to Pakistan. The study tries to fill the gap in the literature with regard to the volatile behavior of various currencies within the context of Pakistan by comparing the exchange rates of its most important trading partners and measuring each in PKR and USD terms. No such study has been conducted: most existing studies focus only on Pakistan's major trading partners fully or partially and compare only a few bilateral exchange rates.

The use of US dollars instead of the domestic currency to perform international transactions can raise issues regarding exchange rate volatility over time. Does the international vehicle currency contribute significantly to the exchange rate volatility of world currencies, and can this be avoided if currencies are exchanged with each other directly without the need for a vehicle currency, i.e., the US dollar?

Further, within the context of Pakistan and its trading partners, there is a need to explore how the exchange of domestic currencies directly against the local currencies of other partners may be more feasible in order to effectively predict future uncertainties that could lead to a volatility hazard during international transactions. This will help decide whether the domestic currency can stabilize the flow of trade and investment or if dependence on a vehicle currency should continue. Our hypothesis is that (i) indirect exchange rates cause a significant rise in volatility compared to domestic rates, and (ii) short-run variations in exchange rates can be forecast more effectively in the case of direct exchange rates.

## 3. Literature Review

There are many methods for measuring exchange rate volatility, ranging from simple standard deviations to the modern GARCH specifications (see Kumar & Dhawan, 1999; Dell'Ariccia, 1999; Clark, Tamirisa, & Wei, 2004). However, these methodologies have certain flaws. The standard deviations method and its applied versions do not incorporate the phenomenon of "volatility clustering" that is usually observed in financial time series or elements of heteroskedastic variance. The moving averages technique yields a bias due to the arbitrarily selected length of its moving average; it also understates the cost of exchange rate changes due to the substantial smoothing of fluctuations, and the deviations from a trend pass through the level of the rate rather than past changes in the rate (Lanyi & Suss, 1982, p. 538). Finally, annual and semiannual rather than monthly changes can be measured through the variability of effective exchange rates (VEER) with a high level of accuracy along with the effective variability (EV) of exchange rates calculated as the weighted sum of the fluctuations in bilateral exchange rates with proportionally assigned weights according to the total number of transactions in each currency (Lanyi & Suss, 1982, pp. 537–538).

Using realized volatility in terms of absolute percentage changes, the lag of standard deviations, or moving average variances would need to follow the assumption of adaptive expectations strictly, i.e., that future values depend solely on past values. However, exchange rate values are usually contained in the present set of information, consequently giving rise to endogeneity (Wang & Barrett, 2002, p. 4). The autoregressive conditional heteroskedasticity (ARCH) model and its generalized versions (GARCH) are found to be more successful in capturing the nonconstant volatility of time-series data, even in the case of one-step-ahead forecastability, compared to most applied autoregressive integrated moving average (ARIMA) models (Sparks & Yurova, 2006, p. 572).

ARCH and GARCH models have been debated extensively in the literature and are considered more effective in generating proxies for volatility variables because of their ability to capture persistence in "shocks" or "news" components, which are observed mainly in financial time series. These models are also more flexible and accurate than others when applied to long time-series data since they allow more precise estimates of the parameters used (Matei, 2009, p. 62).

The error terms in the ARCH model introduced by Engle (1982) have the capacity to encompass the time-varying variance conditional on the past behavior of the same series. Its enhanced version presented by Bollerslev (1986)—the GARCH variance—is able to generate parsimonious models, i.e., those with few parameters and minimum computational effort (see Bollerslev, Chou, & Kroner, 1992; Bollerslev, Engle, & Nelson, 1994). These models are widely used in financial time-series analysis (see, for example, Kroner & Lastrapes, 1993; Grier & Perry, 2000; Arize, 1998).

Most studies have already proved that GARCH (p,q) application is better than any other method of measuring volatility, especially with first lags, i.e., p = 1 and q = 1. In the recent literature that compares GARCH (1,1) with the higher-lag GARCH (p,q) or even other types of volatility models, the former is found to perform better in most cases (Floros, 2008; Tripathy & Gil-Alana, 2010, pp. 1489–1490; Gozgor & Nokay, 2011, pp. 131–132; Vee, Gonpot, & Sookia, 2011, p. 2). Pacelli (2012) finds that, when using GARCH (1,1), GARCH models can better forecast exchange rate dynamics. Many studies support the idea of using the GARCH approach to proxy volatility, perhaps due to the existence of a nonconstant variance.

Al Samara (2009) explains that real exchange rates can change with monetary variables; the autoregressive components of real exchange rates (i.e., the lags) are also highly influential variable(s), especially within time-series specifications. Asseery and Peel (1991) argue that constructing a proxy for exchange rate volatility using the conditional second moment of the given time series has its own economic relevance. Caporale and Doroodian (1994) apply the GARCH (1,1) specification to generate a proxy for the "volatility" of the real exchange rate. Matei (2009) assesses forecasting techniques and evaluates the superiority of advanced complex models by reviewing the 50 most important studies on this subject. He concludes that, as a forecasting model, GARCH is superior to other models, but is sensitive to the frequency of data and performs better when using high-frequency data (pp. 44–45, 62).

Many studies have put forward models with high forecastabilities (see Andersen, Bollerslev, Diebold, & Labys, 2001; Andersen, Bollerslev, Christoffersen, & Diebold, 2006; Engle, 1982, 2001; Engle & Bollerslev, 1986; Engle & Lee, 1999; Engel, Mark, & West, 2007; Franses & McAleer, 2002; Frimpong & Oteng-Abayie, 2006; French, Schwert, & Stambaugh, 1987). Inherent volatility remains unobserved and evolves stochastically over time. Since the mean and variance of this process is subject to certain conditions, it is referred to as the conditional mean and conditional variance:

$y_t = y(t)$ for $t = 1, 2, 3, \dots n$

Conditional mean: $\mu_{t|t-1} = E(y_t|N_{t-1})$

Conditional variance: $\sigma^2_{t|t-1} = var(y_t|N_{t-1}) = E[(y_t - \mu_{t|t-1})^2|N_{t-1}]$

"$N$ = information set" is assumed to incorporate all the relevant information through time lag ($t$ – 1) in the model. If any new information needs to be added to obtain the next interval forecast, then both the mean and conditional variance will deviate in comparison to the next interval mean and variance. The resulting inequality is given as: $\mu_{t|t-1} \neq E(y_t)$ and $\sigma^2_{t|t-1} \neq \mathrm{var}(y_t)$.

Assuming that the unit of time $h = 1$ (i.e., $h > 0$ for discrete intervals) and the exchange rate $ER_{ij}$ = price of the currency of the *i*th country (e.g., PKR) in terms of the currency of the *j*th country (e.g., USD), then $\Pi_j$ = (profit) returns on the currency of the *j*th country, which is quantified as:

$$\Pi_j(t,h) = ER_{ij}(t) - ER_{ij}(t-h) \qquad \text{only if } t > 1$$

Here, risk is represented by the probability of loss in the profit stream from the current period (*t*) to the last period (*h*). As a result, modeling the tradeoff between risk and return becomes essential both for traders and investors when designing financial market policies (Andersen et al., 2006, p. 781).

### *3.1. Status of Exchange Rate Variability in Pakistan*

Pakistan has tried to incorporate some reforms within the financial sector over time, such as making stock markets accessible to a large number of investors and following a flexible exchange rate policy. Since 1970, the rupee has depreciated against the dollar on average from PKR 4.78 to PKR 10.34 in the 1970s, to PKR 17.55 in the 1980s, to PKR 46.82 during the 1990s, and up to PKR 87.16 per dollar during the 2000s. This clearly shows the deteriorating status of the Pakistan rupee, which has lost its effective worth more than 18 times against the dollar in the last four decades.

Historically, Pakistan's foreign exchange system has remained dynamic under fixed and flexible exchange rate regimes. In the beginning, it was pegged to the pound sterling, which continued up to the 1970s in order to keep the exchange rate fixed under the Bretton Woods policy consensus. However, during the early 1970s, the peg-currency (pound sterling) was replaced by the US dollar at PKR 4.76 per USD as an initial exchange rate. The first shock occurred in 1972, when the rupee fell by 56.7 percent in terms of gold. A flexible currency band accommodating fluctuations up to 4.5 percent was introduced to resolve that issue.

From 1981 onward, the exchange rate system shifted from a fixed (pegged) exchange rate to a managed floating system by linking the rupee to a trade-weighted currencies basket. Later, the introduction of a comprehensive package of exchange and payment reforms in the early 1990s permitted domestic residents to open foreign currency accounts within Pakistan. This policy endorsed the legal conversion of the rupee to other currencies in open markets through licensed "currency dealers". The process was smoothed after the acceptance of the IMF obligation in Article VIII (2 to 4) of the IMF Articles of Agreement 1994 (Siddiqui, 2009, pp. 83–84).

Multifaceted exchange rate systems were adopted in 1998 under the flexible exchange rate regime, and comprised three major dimensions: a USD-based exchange rate, a floating interbank exchange rate (FIBR), and a composite (a combination of both rates). Local banks were allowed to declare their own daily exchange rates based on market demand and supply conditions for all currencies except the US dollar, where the exchange rate was required to fall within the band prescribed by the State Bank of Pakistan (SBP). However, in 1999, all three parallel systems were replaced by a single unified exchange rate system, where the rupee was allowed to fluctuate within a range of PKR 52.10 and PKR 52.30 against the US dollar. Although in the early 2000s, when band-limit regulations were abandoned to allow the rupee to float freely, exchange rate determination became the responsibility of market forces (Qayyum & Kemal, 2006).

Kumar and Dhawan (1999) analyze the volatility patterns of Pakistan's export demand from developed countries, and observe that increased exchange rate volatility has an adverse effect on trade. They also find the presence of a "third-country effect" with the use of an international vehicle currency to be significant. This suggests that "exports from Pakistan could be sold in the markets of Japan and (former West) Germany by reallocating them from USA and UK" since these two countries were prime shareholders in exports from Pakistan and resultantly their currencies were sensitive enough to affect Pakistan's balance of payments whenever volatility arose in their respective currencies. However, this argument is weakened when we consider Esquivel and Larraín's (2002) observation that exchange rate volatility in Germany, Japan, and the US leads to higher chances of an exchange rate crisis in developing countries, which were found to be highly susceptible to crisis.

## 4. Data and Methodological Issues

We use data on 28 trading partners of Pakistan[1]. Initially, 40 countries fulfilled the criteria but due to missing values for important variables such as inflation that are needed to calculate the real exchange rate, we have focused only on 29 countries. The time series of exchange rates is measured in real terms based separately on the US dollar and Pakistan rupee for all sampled countries. The data was taken mainly from the IMF's International Finance Statistics. Using two different exchange rate values for each country helps us evaluate which currency performs better in bilateral transactions to facilitate trade and capital flows and avoids volatility distortions by assuming that volatility has an unfavorable impact on trade and investment.

### *4.1. Stationarity*

In the case of time-series analysis, classical linear regression models prove invalid when the time series of selected variables is found to be nonstationary. This is due to the existence of temporal trends because time is a continuous variable and becomes the most prominent determinant of change. Therefore, it is essential to address such issues in time-series variable(s) before applying a classical linear regression model, otherwise the estimates of the coefficients of parameters will not be best, linear, unbiased, efficient (BLUE) estimators, and the results may be spurious.

Making any data stationary means its trend component must be eliminated before using such a series in statistical processing and analysis. Thus, any change in the values of the series if caused solely by the time factor will not be left in the series to exaggerate its explanatory power; if any patterns in the series persist, they will be associated with other factors such as "news" or "shock" that may have a significant influence on the values of the series. Stationarity can be confirmed through first-(or higher) order differentiation of the series.

In this study, we measure volatility in levels on these grounds: (i) poorly estimated models are obtained in many cases when a series is first-differenced in level or log to estimate the GARCH models[2]; (ii) since each

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[1] The major criteria for selecting sample countries is their "relatively significant trade magnitude, i.e., either exports are higher or equal to at least ten million dollars per month on average or imports are more than twenty million US dollars per month on average or both" with Pakistan.

[2] Using first differences can soak up long-run variations, which need to be retained to make an effective analysis. Moreover, negative values of $R^2$ and adjusted $R^2$ were obtained, especially for developing country exchange rates, whether measured in terms of USD or PKR. Finally, the log of the sampled series also held elements of nonstationarity in many cases.

exchange rate has already been regressed on its own first lag, temporal components are automatically controlled to an extent; (iii) in all models that were regressed through classical linear regression, the model misspecification hypothesis was rejected by testing the normality of the residuals.

### *4.2. Estimation Technique*

ARCH models allow the error term to capture a time-varying variance that may be conditional on the past behavior of the same series (Engle, 1982). Bollerslev's (1986) GARCH models are referred to as "parsimonious models" because they minimize the number of parameters and computational efforts required (see Bollerslev et al., 1992; Bollerslev et al., 1994). Many researchers have used these models to analyze financial time series (see Kroner & Lastrapes, 1993; Grier & Perry, 2000; Arize, 1998).

In this study, the time-series data for each exchange rate series is tested to detect autocorrelation in the series by regressing the selected exchange rate variable for each individual country on its own lag series, using ordinary least squares. The statistical significance of these models confirms the strong link between the current value of the *i*th country's exchange rate and its past values. The residuals of these autoregressive models are then analyzed using the Breusch-Pagan-Godfrey serial correlation LM test to determine the existence of white noise, i.e., a zero mean and constant variance. Serial correlation is found in the series when the observed R-squared value proves to be significant on the basis of the chi-squared probability value. The problem of omitted variables is resolved by applying the Ramsey RESET to ensure the model's stability. This helps us confirm the correct specification of the models for statistically insignificant fitted terms (Asteriou, 2006, pp. 114–128).

After taking the residual series of the estimated lagged model, which was selected on the basis of the significance of all its parameters, we apply the autoregressive procedure to the squared residual series to detect the presence of any remaining ARCH effects. If at least one lag term in this squared residual series is found to be statistically significant, this confirms the presence of ARCH effects. Applying the ARCH/GARCH specification is suitable for addressing the problem of conditional heteroskedasticity, but the Breusch-Pagan-Godfrey heteroskedasticity test is also applied to verify the result.

After obtaining a second autoregressive model of residuals for the same series, we generate another residual series—referred to as ″errors of residuals″ to differentiate it from original model's "residual series". This errors-of-residuals series is tested for the normality of the residuals by observing its mean, skewness, kurtosis, and Jarque-Bera (JB) statistics. Theoretically, the mean and skewness should be equal to 0 and the kurtosis should be equal to 3 with insignificant JB statistics to ensure the presence of white noise or to confirm the normality of the residuals. The existence of white noise ensures the validity and efficiency of the estimated coefficients. The exchange rate series for all the sampled countries are selected by applying this procedure to obtain the most valid and efficient models. The GARCH models are also tested with various lag terms, but in many cases GARCH (1,1) successfully fulfills the criteria used to choose the valid models.

### *4.3. GARCH (1,1) Model Specification and Application*

Bollerslev's (1986) GARCH (p,q) model introduces autoregressive and moving average components in the nonconstant variance (Irfan, Irfan, & Awais, 2010, p. 1091). Thus, the mean equation applied in our study is

$$y_t = a + \beta y_{t-1} + u_t$$

$$u_t / \Omega_t \sim iid\ N(0, h_t)$$

The generalized variance equation for GARCH (p,q) is

$$\sum_{j=1}^{q} \gamma_j u_{t-j}^2 + \sum_{i=1}^{p} \delta_i h_{t-i}$$

where, $h_t$ is the nonconstant variance and $\Omega_t$ is the information set, if $\gamma_j + \delta_i < 1$, where $\gamma_j$ and $\delta_i$ must satisfy the nonnegativity condition.

The specific variance equation for GARCH (1,1) is

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \delta_1 h_{t-1}$$

GARCH (1,1) will be stationary only if $\gamma_1 + \delta_1 < 1$.

Accordingly, $h_t$ as a variance scaling parameter depends on the past values of the "shock", i.e., the *p* term, captured by the lagged squared residual term $(u_{t-1}^2)$, and the *q* term, captured by the lagged variance term

$(h_{t-1})$, which reflects the component of "history" (the impact of its own past values on the current value). However, if $p$ increases toward infinity, the ARCH ($p$) specification will become equivalent to the GARCH (1,1) specification. The latter is preferable to a higher-order ARCH that contains a large number of parameters causing a reduction in the degrees of freedom. On the contrary, GARCH (1,1) with a small number of parameters will not cause a great reduction in the degrees of freedom in the model.

GARCH (1,1) models are estimated by imposing a "variance target" restriction on the constant term (Siddiqui, 2009, p. 90), which usually helps to make the constant term a function of the GARCH parameters and unconditional variance by using $\hat{\sigma}^2$ as the unconditional variance of residuals:

$$\gamma_0 = \hat{\sigma}^2\left[1 - \sum_{j=1}^{q} \gamma_j - \sum_{i=1}^{p} \delta_i\right].$$

This is another way of ensuring stationarity by keeping the sum of the ARCH and GARCH terms smaller than the unit $(\gamma_1 + \delta_1 < 1)$. This condition proves to be successful in all cases that involve indirectly measured exchange rate volatility models and in most cases for directly measured exchange rate volatility models. Further, it makes the intercept nonconstant by keeping it as a function of the ARCH and GARCH coefficients.

### *4.4. Methodological Limitations*

Additional specifications for the optimization algorithm and error distribution are applied to both currency-based exchange rates; the optimization algorithm is valid according to the Marquardt algorithm in most cases, but according to the Berndt-Hall-Hall-Hausman (BHHH) algorithm in very few cases. One option is to use a normal (Gaussian) error distribution in each model by assuming that the errors follow a normal distribution; this obtains valid estimations. However, this has been replaced by the Student's t-error distribution or generalized error distribution (GED), where the former specification cannot generate valid estimated models and, consequently, the errors are considered nonnormal.

The Bollerslev-Wooldridge heteroskedasticity-consistent covariance of coefficients restriction is evaluated for each model during estimation but imposed only if the model is significant. Such a restriction essentially "provides correct estimates of the coefficient covariance in the presence of heteroskedasticity of an unknown form;" however, it assumes that serially uncorrelated residuals are obtained through the estimated equation (Agung, 2009, p. 263).

All the models are then compared using the smallest values of the Akaike information criterion (AIC) and Schwarz information criterion (SIC) during estimation to select which is better for each country's exchange rate if more than one model with given specifications is found to be significant. However, the SIC better evaluates the best given models.[3]

In the case of conditional variance models, independent variables with "probability values less than 20 percent (or $p < 0.20$) allowed us to conclude that the concerned variable(s) imparts a significant effect on the dependent variable at 10 percent level of significance" (Agung, 2009, p. 440). In this case, the models are selected using the same guidelines, but by exploiting all the possible options we can identify highly significant models to derive all volatility proxy variables in the form of a GARCH variance series.

## 5. Results, Analysis, and Limitations

### *5.1. GARCH (1,1) Model-Based Exchange Rate Volatilities: Graphical Analysis*

Figure A2 in the Appendix illustrates all GARCH (1,1) based volatilities, giving developed countries' and developing countries' exchange rates separately. Each graph shows volatility measured both in terms of foreign (upper line) and domestic currency value (lower line)-based exchange rates. All the volatility variables are compared graphically by taking their respective natural logarithms to smooth any intensities, as observed in some cases.

Figure 2 compares the exchange rate volatilities of developed and developing countries; the direct bilateral exchange rates reveal that the standard deviation of volatilities is larger for virtually all developed countries. Since the developed countries included in the sample are those with whom most developing countries have extensive trade links (and that are also major trading partners of Pakistan), short-run forecasting may be required to avoid potential losses in international transactions.

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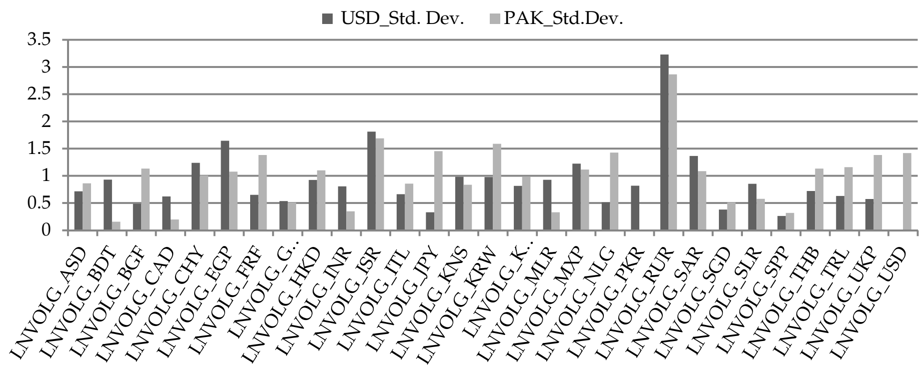
[3] The SIC is an alternative to the AIC but "imposes a larger penalty for an additional coefficient used in the model" (Agung, 2009, p. 28). Hence, it is preferred to the AIC.

**Figure 2: Comparison of standard deviations for PKR- and USD-based exchange rate volatilities**




All the volatility series are given in Figure A2. Some important results and observations are given in Table A1 (see Appendix 1). Those currencies for which the average volatility margins are greater than one standard deviation include the Indonesian rupiah, Russian ruble, and South African rand for both direct and indirect rates; the German deutschemark, Singapore dollar, and Spanish peseta indicate standard deviation variations of less than 0.5.

The trends are more obvious in domestic currency value-based exchange rate volatilities, where 11 currencies follow a downward trend while two currencies, the Korean won and Russian ruble, show cyclical trends. Some of the currencies contained comparatively lower volatility in domestic currency value based rates like Bangladeshi taka, Canadian dollar, Chinese yuan, Egyptian pound, Indian rupee, Indonesian rupiah, Kenya shilling, Malaysian ringgit, Mexican peso, Russian ruble, South African rand, and Sri Lankan rupee.

Recurrent spikes and high levels of fluctuation are observed in those currencies where the exchange rates are more volatile. The presence of high "volatility clustering" is also evident. The graphical analysis reveals that the volatility series generally remains stationary in most cases, although a marginal or considerable trend emerges in some cases. The volatility spikes are usually found to coincide at a particular point in time in both exchange rates terms, implying that the use of an international currency may not be the only cause of fluctuation.

**Table 1: Currencies prove consistent segment-wise with respect to all four methods of error measurement and forecastabilities**

| | Exchange rates | |
|---|---|---|
| **Forecastability** | **Domestic rates (PKR)** | **Foreign rates (USD)** |
| Highly effective (top segment only) | Kuwaiti dinar, Canadian dollar, US dollar | Kuwaiti dinar, Canadian dollar, Singapore dollar |
| Very good (top and middle) | Hong Kong dollar, Malaysian ringgit | Hong Kong dollar, Malaysian ringgit |
| Good (middle segment only) | Spanish peseta, Australian dollar, Singapore dollar, Chinese yuan | Spanish peseta, Australian dollar |
| Fairly (mostly in middle segment) | Egyptian pound | Egyptian pound, Dutch guilder |
| Poorly (lower segment only) | Mexican peso, Japanese yen, Russian ruble, Indonesian rupiah | Japanese yen, Russian ruble, Indonesian rupiah<br>Kenyan shilling, Korean won |

Interestingly, the mean of the volatility series is lower for domestic currency-valued exchange rates than for foreign ones. The exchange rate volatility for domestic rates is mostly not normally distributed—it is negatively skewed in the case of the Bangladeshi taka, Canadian dollar, Indian rupee, Malaysian ringgit, and Spanish peseta, and positively skewed for the German deutschmark, Italian lira, Kenyan shilling, Mexican peso, and Sri Lankan rupee.

### *5.2. GARCH (1,1) Model-Based Exchange Rate Volatilities: Analysis of Results*

Since invertible series possess the property of convergence, where the sum of the coefficients of both the ARCH and GARCH terms in the models must be less than unity, all the exchange rate volatilities are evaluated in both currency terms. The conditional distribution of errors is initially assumed to be normal (Gaussian), but we also apply the Student's t-distribution and GED to obtain valid models. The Marquardt algorithmic option helps achieve convergence in most cases, as compared to the BHHH algorithm. All foreign currency-valued exchange rate series converge earlier than domestic ones.

During estimation, we attempt to construct models by applying the Bollerslev-Wooldridge (1992) method of heteroskedasticity-consistent covariance, which allows the computation of quasi-maximum likelihood covariance and standard errors, usually needed if the residuals fail to become conditionally normally distributed (Floros, 2008, p. 37). However, in some cases, the normally distributed error does not have this property; those models are then considered fit to generate volatility proxies that contain each parameter of mean and variance equations, which are significant at the 10 percent level.

The significance of all GARCH (1,1)-based volatility models in both currency terms shows that volatility clustering plays an important role in causing monthly changes in the exchange rates. Andersen et al. (2001), who present strong evidence of the volatility clustering impact on daily returns, support this observation. This means that the impact of any kind of "shock" takes more time to taper off.

The detailed results for all 28 foreign currency-valued exchange rate volatility models are given in Table A2; the domestic currency-valued exchange rate volatility models are presented in Table A3 (see Appendix 1). Many exchange rate volatility models are found to rapidly converge, requiring a small number of iterations, and are found to be invertible. Most of the foreign currency-valued exchange rate variances remain rapidly convergent compared to domestic ones.

Those exchange rate series that are found to be explosive (with a higher degree of volatility and divergence) include the Indonesian rupiah, Kenyan shilling, Pakistani rupee, and Russian ruble in terms of foreign currency-valued exchange rate volatility; and the Canadian dollar, Indian rupee, Indonesian rupiah, Korean won, and Malaysian ringgit in terms of domestic currency-valued exchange rate volatilities. One of the reasons for this divergence is that the variance-targeted constant term restriction has to be withdrawn to obtain better model specifications with highly significant parameters, but the domestic currency-valued Canadian dollar and Indian rupee exchange rate volatility models remain explosive even in the presence of this restriction.

All foreign currency-valued exchange rate models prove to be significant when estimated assuming a normal (Gaussian) distribution of errors. Exceptions include the Chinese yuan, where the GED needs to be considered, and the Kuwaiti dinar and Egyptian pound, where the Student's t-error distribution is applied to obtain a valid model. In the same way, we estimate direct exchange rate models assuming a normal (Gaussian) distribution of errors, except for the Bangladeshi taka, Canadian dollar, and Hong Kong dollar, which remain valid and significant assuming a Student's t-error distribution. The Egyptian pound, Indian rupee, Italian lira, Kenyan shilling, Kuwaiti dinar, and Mexican peso have a GED. This shows that indirect exchange rate volatility models are usually more stable and consistent than direct exchange rate volatility models.

In Tables A2 and A3, the sum of the estimators' coefficient values in each GARCH-based conditional volatility model is close to unity, indicating the persistence of volatility shocks. Generally, all the volatility models are found to be highly significant and show positive values for each coefficient of lagged exchange rates in the mean equation. In addition, the coefficient of the lagged conditional variance is also significant and usually has a positive sign but is less than 1, implying that last-period news can still have a significant impact on volatility.

We find evidence of long memory in variances through the large magnitude of the GARCH coefficients, such as for the Bangladeshi taka, Canadian dollar, French franc, Indian rupee, Japanese yen, Malaysian ringgit, Dutch guilder, Spanish peseta, and Turkish lira, in terms of domestic rates. In terms of foreign rates, this is observed in the case of the Belgium franc, Canadian dollar, French franc, German deutschmark, Hong Kong dollar, Japanese yen, Kuwaiti dinar, Dutch guilder, and Spanish peseta. Interestingly, in the case of developed partners, the long memory effect is found to be persistent and more visible.

### *5.3. Predictability of GARCH (1,1) Model-Based Exchange Rate Volatilities*

Four major evaluation criteria (loss functions) are applied to compare the volatility of each currency-based exchange rate including: RMSE, MAE, MAPE, and TIC. The reason for applying all four criteria is to obtain consistent and vigorous results regarding the forecastability of GARCH (1,1)-based exchange rate volatility models.[4] The RMSE usually gives more weight to large forecast errors while the MAE gives equal weight to both over- and under-predicted values of volatility forecasts (Vee et al., 2011, p. 10).

The RMSE and MAE also help measure those forecasts that are conditional on the scale of the dependent variables, and allow one to compare relative forecasts for the same series across various models. The minimum forecasting error measured through a given loss function indicates the superior forecasting ability of a particular model. The MAPE and TIC are both scale-independent, where the TIC lies between 0 and 1, with 0 denoting the perfect fit (Ocran & Biekpe, 2007, p. 96).

[4] Various studies have applied and tested these criteria to evaluate both the static (short-run) and dynamic (long-run) forecastabilities of time series models (see Vee et al., 2011; Matei, 2009; Frimpong & Oteng-Abayie, 2006; Sparks & Yurova, 2006; Zivot, 2008).

The versatility of these loss functions helps us identify and differentiate between those currencies that have high predictive power and those with poor predictive power. In this case, all the sampled countries are divided into three different segments by assigning each country a rank based on the minimum values obtained through each criterion of evaluation, referred to as the top, middle, and lower segments, respectively. The top segment includes eight countries with the highest position in terms of their respective performance in one-step-ahead forecasts based on each criterion. These countries fall in the "highly effective forecasting" category where robust and effective short-run forecasting of variations in their bilateral exchange rates is possible, especially when Pakistan is a trading partner.

The remaining 20 countries are divided into two equal segments. The middle segment includes the ten countries next in rank by assuming that their currencies can be reasonably well forecast, and so including them in the "very good" category. The lower segment comprises ten other countries at the lowest level of forecastability, which are included in the "poor" category, referring those currencies that perform poorly in forecasting short-run variations in exchange rates. Tables A4 and A5 (Appendix 2) identify all the sampled countries and their respective currencies in each category on the basis of each loss function.

Table 1 shows that roughly the same currencies have consistently acquired the same, or close to the same, rank in the case of each (loss function) evaluation criterion, and remained part of a common segment. Exchange rates are measured using two different bases, i.e., the Pakistan rupee as the domestic and US dollar as the foreign currency value. The consistency of these results shows that GARCH (1,1)-based volatility models strongly help to predict variations in both the Kuwaiti dinar and Canadian dollar, irrespective of the base currency; US dollar exchange rate volatility measured in domestic currency value terms; and Singapore dollar exchange rate volatility measured in foreign currency value terms. Consequently, Pakistan could shield the potentially negative effect on trade and business scenario—usually more sensitive to a volatile currency exchange rate—by using GARCH (1,1) forecasting models when making international transactions primarily through Kuwaiti dinars, Canadian dollars, and US dollars directly.

Using the Hong Kong dollar and Malaysian ringgit is equally good because GARCH (1,1)-based volatilities can effectively capture the uncertain variability in the exchange rates of these currencies, at least in the short run. Further, the ability to predict future variations and uncertainties in exchange rates with a high level of accuracy in the shape of "shocks" or "news" is in great demand by traders and investors. This could be made available through the GARCH (1,1) model in terms of various currencies for traders and investors, especially those from Pakistan, and also for the country's significant trading partners. The Egyptian pound, Mexican peso, Japanese yen, Russian ruble, and Indonesian rupiah are not, however, considered feasible for conducting direct international transactions due to their poor forecastability and high deviations from the mean.

The overall statistics obtained through the MAE are lower than the RMSE. No perfect-fit models could be obtained based on the TIC statistics because, although the TIC values are close to 0, none of them is equal to 0. Further, the similar ranks assigned to each country/currency according to the given forecasting evaluation criteria clearly reveals that, to an extent, these criteria are reasonably valid substitutes for one another. Hence, they need not be used simultaneously to save time and effort. The RMSE and MAE both assign the same ranks to various exchange rate volatility models, irrespective of the base currencies, and therefore are preferred to the MAPE and TIC when measuring short-run predictive capacity.

## 6. Major Findings, Policy Implications, and Conclusions

Our main findings are described below.

First, foreign currency-valued exchange rate volatilities converge more rapidly than domestic ones, which implies that the former have a linear structure compared to the latter models in which forecasting is possible and easy.[5] Second, volatility spikes remain independent of the base currency used to calculate exchange rate volatilities. This implies that foreign currency-valued exchange rates are not the major cause of various shocks in financial markets.

Third, those exchange rate volatilities that remain explosive in both currency terms are poor at making one-step-ahead forecasts, with the exception of the Canadian dollar. This confirms the first finding that the parameters of explosive models are nonlinear where accurate forecasting is difficult. We can conclude that rapid convergence and stationarity are required to make effective forecasts because those models in which the ARCH and GARCH terms fail to achieve stationarity remain explosive,

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[5] Rapid convergence shows a linearity of equations with respect to the parameters because linear equation estimation needs only one iteration to converge (SAS Institute, 1999, p. 742).

which can also decrease their forecasting ability. Fourth, various forecasting evaluation criteria are usually consistent in terms of results and consequent rank assignment.

Fifth, the RMSE and MAE are better at assigning ranks to various currencies in the sample according to their respective forecastabilities. Sixth, using an international currency instead of a domestic currency to perform international transactions does not make exchange rates more volatile, therefore contradicting our first hypothesis.

Since policymakers are interested in keeping the exchange rate more certain and less volatile in the future, this purpose may be served in the short run by using GARCH-based exchange rate volatility models because exchange rate series, like other financial time-series, exhibit two main properties: fat tails and volatility clustering.[6] Hence, GARCH models, usually with a first lag, are considered suitable for resolving the issues above and helpful in understanding the dynamics of an exchange rate series.

The analysis of two different currency-based exchange rate volatilities has clearly revealed that, at least in the context of Pakistan, the use of US dollars as an international currency is beneficial because it ensures rapid adjustment in exchange rate variations in various currencies without compromising their stability against the Pakistan rupee. The use of an international (vehicle) currency can also have a "third-country effect", as observed by Cushman, which intensifies the exchange rate volatility because of the "correlation of exchange rate fluctuations" (1986, p. 1226) when developing countries use it instead of their own domestic currency. However, this could not be covered within the scope of this study and should be considered for future research.

The application and comparison of four different loss functions to measure the predictive capacity of various models proves that the RMSE and MAE techniques are superior to other techniques. Since the Kuwaiti dinar, Canadian dollar, US dollar, Singapore dollar, Hong Kong dollar, and Malaysian ringgit can be effectively forecast at least in the short run, they are preferred for international transactions. This helps address uncertainties and the temporal self-dependence of exchange rate volatilities and prevents potential losses in international transactions. Given that the use of an international (vehicle) currency is not the main contributor to volatility, continuing to use the US dollar to conduct international transactions is beneficial for Pakistan with respect to all its significant trading partners.

[6] Floros's (2008) "fat tail" reflected different degrees of leptokurtosis for the same variance.

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# *Appendix 1*

## Results of GARCH (1,1)-based volatility models

### Table A1: Graphical analysis of GARCH (1,1)-based volatilities

| Currency | Average volatility margins (standard deviation) | | Trend (frequency of fluctuations) | | Highly volatile (spikes) years (period) | |
|---|---|---|---|---|---|---|
| | PKR | USD | PKR | USD | PKR | USD |
| Australian dollar (ASD) | 0.001123 | 0.033153 | No (H)* | @Up (H*) | 72-74, 77, 83, 85, 86, 08-09 | 73, 74, 77, 83, 85, 86, 98, 01-02, 09 |
| Bangladeshi taka (BDT) | 0.032343 | *0.725098* | No | @Down(H) | No | 75, 85, 90, 01-02, 06-07 |
| Belgian franc (BGF) | 0.000796 | 0.022032 | Down (H) | No (M) | 72-74, 81, | 82, 85 |
| Canadian dollar (CAD) | 0.00133 | 0.015067 | No | Up (L) | 72 | 09 |
| Chinese yuan (CHY) | 0.004714 | 0.196466 | @Down (H) | @Up (H*) | 72-74, 78, 94-95 | 72, 78, 94 |
| Egyptian pound (EGP) | 0.004628 | 0.102956 | No (M) | No (H) | 72-74, 79-81, 90-92, 03 | 74-75, 79-81, 90-92, 95, 01, 03-04, 08 |
| French franc (FRF) | 0.000941 | 0.020766 | Down (M) | No (M) | 72-73 | No |
| German deutschmark (GDM) | 0.000949 | 0.021598 | No (H*) | No (L) | 71, 72, 73-74, 81, 84 | 73 |
| Hong Kong dollar (HKD) | 0.004573 | 0.087218 | No (M) | @Up (M) | 72-74, 80, 81-84, 89-90 | 73-74, 79-81, 83-84, 05 |
| Indian rupee (INR) | 0.02109 | 0.639649 | No | @Up (H*) | No | 92, 93, 95-96 |
| Indonesian rupiah (ISR) | *9.773622* | *390.4742* | No (H*) | No (H*) | 72, 74, 79, 82, 83, 86, 98-99, 01-02, 09. | 70, 72, 73, 79, 83, 86, 97-98, 01, 06, 09 |
| Italian lira (ITL) | 0.00083 | 0.020386 | @Down(H*) | No (H)* | 72-74, 76, 81 | 74, 76, 85-86, 93, 97, 01, 09 |
| Japanese yen (JPY) | 0.140736 | *3.285553* | Down (H) | No (M) | 72-73, 86, 95, 98 | 71 |
| Kenyan shilling (KNS) | 0.080893 | *2.369582* | No (H*) | @Cyclical(H*) | 72, 76, 81-82, 93, 95-96, 98 | 75, 76, 81-82, 84, 93-95, 98, 03, 06 |
| Korean won (KRW) | *1.233907* | *21.38206* | Cyclical(H*) | No (H)* | 71-73, 74-75, 76,80-81, 83, 89, 94, | 71, 74, 80, 98-99, 01, 08-09 |

| **Currency** | **Average volatility margins (standard deviation)** | | **Trend (frequency of fluctuations)** | | **Highly volatile (spikes) years (period)** | |
|---|---|---|---|---|---|---|
| | | | | | 96, 98-99, 01, 08-09 | |
| Kuwaiti dinar (KWD) | 1.79E-04 | 0.003537 | No (M) | No (M) | 71-74, 79-80, 83 | 79-80, 89 |
| Malaysian ringgit (MLR) | 0.002801 | 0.039892 | No | No (H*) | 72 | 73, 75, 80, 92, 94, 98-99 |
| Mexican peso (MXP) | 0.014758 | 0.49483 | No (H*) | No (H)* | 72, 77, 81-83, 86, 88, 95, 98, 09 | 77, 81-83, 86-87, 95-96, 98, 09 |
| Dutch guilder (NLG) | 0.001032 | 0.022348 | Down (L) | No (L) | 72, 81-82 | 74, 82, 85-86 |
| Pakistani rupee (PKR) | __ | 0.997572 | __ | No (H*) | __ | 72, 73, 89, 93, 95, 97, 99,01 |
| Russian ruble (RUR) | *0.166004* | *7.815225* | Cyclical (H*) | Cyclical (H*) | 72, 82, 92-94, 98-99, 09 | 72, 92-94, 96, 97, 98-99, 2000-01, 09 |
| South African rand (SAR) | 0.005836 | 0.188274 | @Down(H)* | Up (H*) | 72, 76, 81, 84-86, 98, 02-03, 09 | 72-73, 76, 84-86, 95, 98, 02-03, 09 |
| Singapore dollar (SGD) | 0.001527 | 0.021871 | No (H*) | No (M) | 71, 72, 75, 79 | 73-74, 98 |
| Sri Lankan rupee (SLR) | 0.077471 | *1.942905* | No (H*) | No (H*) | 72, 78, 79, 81-82, 90 | 77-78, 80, 81, 83, 89, 93, 95, 98, 02, 05, 07 |
| Spanish peseta (SPP) | 0.001546 | 0.022663 | No | No (L) | 72* | No |
| Thai Land Baht (THB) | 0.025838 | 0.584162 | Down (H*) | No (M-H*) | 72, 80, 81, 85, 98-99, 2001 | 81, 85, 98-99, 2001, 07 |
| Turkish lira (TRL) | 0.002733 | 0.078735 | Down (M) | No (M) | 71, 72, 80, 94-95, 01-02 | 71, 80, 94-95, 01-02 |
| United Kingdom pound (UKP) | 0.000735 | 0.015928 | Down (H)* | No (H)* | 72-73, 81, 84-85, 89, 93, 97, 09 | 79, 85, 93, 09 |
| United States dollar (USD) | 0.000706 | __ | Down(H)* | __ | 72 | __ |

Note: Graphs were drawn in logarithmic transformation but the values were used in level in this table, therefore representing the deviation from the mean at the original level of measurement.

Level of frequencies: @ = at margin, H = high, M = medium, L = low.

* Significantly observable volatility clustering within brackets if compatible with frequency, otherwise placed outside brackets.

## Table A2: GARCH (1,1): USD-based models

| RER_country | ARCH coefficient ($\gamma_1$) (z-statistics) | GARCH coefficient ($\delta_1$) (z-statistics) | Optimization algorithm^ | $\sum(\gamma_j + \delta_i)$ | Convergent/ explosive (No. of iterations) |
|---|---|---|---|---|---|
| RERD_ASD | 0.284651 (4.10)* | 0.596191 (5.78)* | Marquardt | 0.880842 <1 | Convergent-45 |
| RERD_ BGF | 0.096275 (2.63)* | 0.858712 (16.24)* | Marquardt | 0.954987 <1 | Convergent-18 |
| RERD_ BDT | 0.216256 (4.34)* | 0.745320 (10..72)* | Marquardt | 0.961576 <1 | Convergent-237 |
| RERD_ CAD | 0.042615 (2.65)* | 0.953193 (51.59)* | Marquardt | 0.995808 <1 | Convergent-11 |
| RERD_ CHY [GED@2.5] | 0.783574 (23.67)* | 0.116985 (2.98)* | Marquardt | 0.900559<1 | Convergent-131 |
| RERD_ EGP [t@10] | 0.279262 (17.71)* | 0.718244 (44.43)* | Marquardt | 0.997506<1 | Convergent-29 |
| RERD_ FRF | 0.107337 (3.82)* | 0.868634 (23.89)* | Marquardt | 0.975971<1 | Convergent-19 |
| RERD_ GDM | 0.106903 (2.70)* | 0.854000 (16.77)* | Marquardt | 0.960903 <1 | Convergent-10 |
| RERD_ HKD | 0.102602 (4.46)* | 0.873107 (37.30)* | Marquardt | 0.975709 <1 | Convergent-29 |
| RERD_ INR | 0.315616 (7.30)* | 0.598453 (9.70)* | Marquardt | 0.914069 <1 | Convergent-238 |
| RERD_ ISR | 1.787072 (3.36)* | 0.165427 (2.61)* | Marquardt, without restricted constant term | 1.952499 >1 | Explosive-862 |
| RERD_ ITL | 0.203095 (4.78)* | 0.741284 (12.69)* | Marquardt | 0.944379 <1 | Convergent-14 |
| RERD_ JPY | 0.058305 (1.79)** | 0.904221 (14.08)* | BHHH | 0.962526 <1 | Convergent-51 |
| RERD_ KNS | 0.379841 (2.55)* | 0.623122 (5.23)* | Marquardt, without restricted constant term | 1.002963 >1 | Explosive-50 |
| RERD_ KRW | 0.583274 (3.01)* | 0.326481 (1.58) ** | BHHH | 0.909755 <1 | Convergent-43 |
| RERD_ KWD [t@10] | 0.081725 (5.86)* | 0.906066 (58.20)* | Marquardt | 0.987791<1 | Convergent-74 |
| RERD_ MXP | 0.337620 (2.75)* | 0.636507 (4.71)* | Marquardt | 0.974127 <1 | Convergent-59 |
| RERD_ MLR | 0.621868 (7.21)* | 0.276835 (2.44)* | Marquardt | 0.898703 <1 | Convergent-56 |
| RERD_ NLG | 0.094233 (2.79)* | 0.867497 (22.51)* | Marquardt | 0.96173 <1 | Convergent-13 |

| **RER_country** | **ARCH coefficient ($\gamma_1$) (z-statistics)** | **GARCH coefficient ($\delta_1$) (z-statistics)** | **Optimization algorithm^** | $\sum(\gamma_j + \delta_i)$ | **Convergent/ explosive (No. of iterations)** |
|---|---|---|---|---|---|
| RERD_ PKR | 1.430321 (1.67)** | -0.008884 (-11.79)* | Marquardt, without restricted constant term | 1.421437 >1 | Explosive-38 |
| RERD_ RUR | 3.682844 (2.46)* | 0.076209 (1.68)** | Marquardt, without restricted constant term | 3.759053 >1 | Explosive-96 |
| RERD_ SAR | 0.279295 (4.01)* | 0.705559 (9.46)* | Marquardt | 0.984854 <1 | Convergent-33 |
| RERD_ SLR | 0.775119 (2.98)* | 0.194128 (2.78*) | Marquardt, without restricted constant term | 0.969247 <1 | Convergent-30 |
| RERD_ SGD | 0.139742 (2.26)* | 0.701444 (6.49)* | Marquardt | 0.841186 <1 | Convergent-15 |
| RERD_ SPP | 0.041490 (1.56)** | 0.907352 (16.13)* | Marquardt | 0.948842 <1 | Convergent-11 |
| RERD_ THB | 0.285579 (1.88)** | 0.478501 (3.69)* | Marquardt, without restricted constant term | 0.76408 <1 | Convergent-190 |
| RERD_ TRL | 0.131245 (20.00)* | 0.799107 (76.34)* | Marquardt (without RSE) | 0.930352 <1 | Convergent-82 |
| RERD_ UKP | 0.226794 (5.05)* | 0.663268 (8.97)* | Marquardt | 0.890062 <1 | Convergent-14 |

Note: ^ = Marquardt algorithmic optimization was applied but where coefficients proved insignificant, BHHH (Berndt-Hall-Hall-Hausman) was tested. Further heteroskedasticity-consistent covariance (Bollerslev-Wooldridge) was used. Constant term in all models was restricted as a function of the GARCH parameters and unconditional variance. All models are stationary except USD-based PKR.
* Significant at 5%, ** at 10%.

## Table A3: GARCH (1,1): PKR-based models

| RER_country [error distribution] | ARCH coefficient ($\gamma_1$) (z-statistics) | GARCH coefficient ($\delta_1$) (z-statistics) | Optimization algorithm^ | $\sum(\gamma_j + \delta_i)$ | Convergent/ explosive (No. of iterations) |
|---|---|---|---|---|---|
| RERR_ASD | 0.849144 (29.14)* | -0.008907 (-10..29)* | Marquardt | 0.840237<1 | Convergent-51 |
| RERR_ BGF | 0.200190 (6.68)* | 0.793676 (25.97)* | Marquardt | 0.993866<1 | Convergent-207 |
| RERR_ BDT [Student's t] | 0.014725 (3.60)* | 0.979600 (183.7)* | Marquardt | 0.994325<1 | Convergent-17 |
| RERR_ CAD [Student's t] | 0.000876 (3.68)* | 0.999913 (6545)* | BHHH | 1.000789>1 | Explosive-30 |
| RERR_ CHY | 0.204335 (4.41)* | 0.766797 (12.78)* | Marquardt | 0.971132<1 | Convergent-234 |
| RERR_ EGP [GED] | 0.137942 (3.42)* | 0.838840 (17.39)* | Marquardt | 0.976782<1 | Convergent-34 |
| RERR_ FRF | 0.101547 (8.20)* | 0.896949 (71.16)* | Marquardt | 0.998496<1 | Convergent-175 |
| RERR_ GDM | 0.626305 (7.13)* | -0.164023 (-30.72)* | Marquardt | 0.462282<1 | Convergent-52 |
| RERR_ HKD [Student's t] | 0.180939 (4.95)* | 0.800635 (20.32)* | Marquardt | 0.981574<1 | Convergent-63 |
| RERR_ INR [GED] | 0.001626 (3.23)* | 0.998588 (1984)* | Marquardt | 1.000214>1 | Explosive-88 |
| RERR_ ISR | 1.662280 (5.58)* | 0.174667 (4.24)* | Marquardt, without restriction | 1.836947>1 | Explosive-30 |
| RERR_ ITL [GED] | 0.210044 (3.83)* | 0.757048 (11.30)* | Marquardt | 0.967092<1 | Convergent-101 |
| RERR_ JPY | 0.144470 (5.54)* | 0.853663 (32.52) | Marquardt | 0.998133<1 | Convergent-104 |
| RERR_ KNS [GED] | 0.444142 (7.59)* | 0.472030 (6.57)* | Marquardt | 0.916172<1 | Convergent-21 |
| RERR_ KRW | 1.809092 (2.06)* | 0.379925 (3.00)* | Marquardt, without restriction | 2.189017>1 | Explosive-63 |
| RERR_ KWD [GED] | 0.174085 (3.90)* | 0.805181 (15.07)* | Marquardt | 0.979266<1 | Convergent-95 |
| RERR_ MXP [GED] | 0.582858 (7.61)* | 0.354729 (4.12)* | Marquardt | 0.937587<1 | Convergent-32 |
| RERR_ MLR | 0.007827 (5.08)* | -0.622043 (-6.65)* | Marquardt | -0.614216<1 | Convergent-26 |
| RERR_ NLG | 0.099376 (8.37)* | 0.899490 (73.67)* | Marquardt | 0.998866<1 | Convergent-197 |
| RERR_ RUR | 0.813796 (10.15)* | 0.185714 (2.31)* | Marquardt | 0.99951<1 | Convergent-24 |

| RER_country [error distribution] | ARCH coefficient ($\gamma_1$) (z-statistics) | GARCH coefficient ($\delta_1$) (z-statistics) | Optimization algorithm^ | $\sum(\gamma_j + \delta_i)$ | Convergent/ explosive (No. of iterations) |
|---|---|---|---|---|---|
| RERR_ SAR | 0.274207 (4.27)* | 0.702237 (9.71)* | Marquardt | 0.976444<1 | Convergent-108 |
| RERR_ SLR | 0.435121 (1.96)* | 0.255231 (3.25)* | Marquardt | 0.690352<1 | Convergent-246 |
| RERR_ SGD | 0.658353 (4.47)* | -0.181195 (-26.42)* | Marquardt | 0.477158<1 | Convergent-182 |
| RERR_ SPP | 0.004589 (1.87)** | -0.860440 (-2.80)* | Marquardt | -0.85585<1 | Convergent-29 |
| RERR_ THB | 0.430015 (5.93)* | 0.530468 (7.67)* | Marquardt | 0.960483<1 | Convergent-130 |
| RERR_ TRL | 0.090596 (2.52)* | 0.903255 (21.27)* | BHHH | 0.993851<1 | Convergent-57 |
| RERR_ UKP | 0.313476 (3.52)* | 0.675075 (7.37)* | Marquardt | 0.988551<1 | Convergent-165 |
| RERR_ USD | 0.485640 (4.06)* | 0.497765 (4.01)* | Marquardt | 0.983405<1 | Convergent-141 |

Notes: Restriction of variance target was imposed because the constant term in all models was restricted as a function of the GARCH parameters and unconditional variance. Heteroskedasticity-consistent covariance (Bollerslev-Wooldridge) was also used with this restriction. All models are stationary except PKR-based ASD, CAD, GDM, MLR, SGD, and SPP.

^ = Marquardt algorithmic optimization was preferred because in many cases either the coefficients proved to be insignificant or the iteration failed to improve after a specific level in the case of BHHH (Berndt-Hall-Hall-Hausman).

* Significant at 5%, ** at 10%. Only significant models reported.

# *Appendix 2*

## Ranking of sampled countries/currencies: GARCH (1,1) models-based one-step-ahead forecastabilities

### Table A4: GARCH (1,1)-based volatility models: Ranking for one-step-ahead forecastabilities

| Rank | Country | RMSE | Country | MAE | Country | MAPE | Country | TIC |
|---|---|---|---|---|---|---|---|---|
| 1 | RERR_KWD | 0.000260 | RERR_KWD | 0.000104 | RERR_HKD | 1.539356 | RERR_ BDT | 0.013929 |
| 2 | RERR_ UKP | 0.001074 | RERR_ ITL | 0.000510 | RERR_MLR | 1.633824 | RERR_ HKD | 0.016957 |
| 3 | RERR_GDM | 0.001183 | RERR_ CAD | 0.000529 | RERR_KWD | 1.647312 | RERR_ INR | 0.017833 |
| 4 | RERR_ ITL | 0.001192 | RERR_ USD | 0.000543 | RERR_BDT | 1.667074 | RERR_KWD | 0.019563 |
| 5 | RERR_ BGF | 0.001228 | RERR_GDM | 0.000551 | RERR_INR | 1.700491 | RERR_ CAD | 0.019992 |
| 6 | RERR_ USD | 0.001273 | RERR_ BGF | 0.000561 | RERR_CAD | 1.740250 | RERR_ SLR | 0.020061 |
| 7 | RERR_ FRF | 0.001274 | RERR_ UKP | 0.000570 | RERR_USD | 1.741950 | RERR_ MLR | 0.020412 |
| 8 | RERR_ CAD | 0.001341 | RERR_ SPP | 0.000595 | RERR_SGD | 1.759509 | RERR_ USD | 0.021910 |
| 9 | RERR_ NLG | 0.001401 | RERR_ FRF | 0.000675 | RERR_KRW | 2.000351 | RERR_ CHY | 0.021970 |
| 10 | RERR_ SPP | 0.001549 | RERR_ NLG | 0.000720 | RERR_THB | 2.132959 | RERR_ ITL | 0.022647 |
| 11 | RERR_ ASD | 0.001810 | RERR_ SGD | 0.000756 | RERR_ITL | 2.215917 | RERR_ SGD | 0.023210 |
| 12 | RERR_ SGD | 0.002009 | RERR_ ASD | 0.000860 | RERR_SLR | 2.223079 | RERR_ ASD | 0.023622 |
| 13 | RERR_ MLR | 0.002806 | RERR_ MLR | 0.001104 | RERR_EGP | 2.264776 | RERR_GDM | 0.023682 |
| 14 | RERR_ TRL | 0.003335 | RERR_ TRL | 0.001510 | RERR_CHY | 2.286328 | RERR_ BGF | 0.024206 |
| 15 | RERR_ EGP | 0.006133 | RERR_ EGP | 0.002210 | RERR_SPP | 2.288698 | RERR_ THB | 0.024546 |
| 16 | RERR_ CHY | 0.006272 | RERR_ HKD | 0.002780 | RERR_KNS | 2.319876 | RERR_ KNS | 0.024589 |
| 17 | RERR_ HKD | 0.006383 | RERR_ CHY | 0.003171 | RERR_ASD | 2.373710 | RERR_KRW | 0.024608 |
| 18 | RERR_ SAR | 0.007620 | RERR_ SAR | 0.004214 | RERR_BGF | 2.379223 | RERR_ SPP | 0.025290 |
| 19 | RERR_ MXP | 0.025347 | RERR_ MXP | 0.008784 | RERR_GDM | 2.443351 | RERR_ FRF | 0.025849 |
| 20 | RERR_ INR | 0.029983 | RERR_ INR | 0.013485 | RERR_MXP | 2.574731 | RERR_ UKP | 0.026213 |
| 21 | RERR_ BDT | 0.032649 | RERR_ BDT | 0.017255 | RERR_JPY | 2.584721 | RERR_ NLG | 0.026428 |
| 22 | RERR_ THB | 0.040099 | RERR_ THB | 0.018414 | RERR_FRF | 2.702764 | RERR_ SAR | 0.026472 |
| 23 | RERR_ SLR | 0.093295 | RERR_ SLR | 0.047559 | RERR_NLG | 2.726639 | RERR_ JPY | 0.027108 |
| 24 | RERR_ KNS | 0.119986 | RERR_ KNS | 0.050698 | RERR_UKP | 2.775656 | RERR_ EGP | 0.029277 |
| 25 | RERR_ JPY | 0.229584 | RERR_ JPY | 0.094110 | RERR_SAR | 2.856873 | RERR_ TRL | 0.035374 |
| 26 | RERR_ RUR | 0.363728 | RERR_ RUR | 0.155388 | RERR_TRL | 3.340640 | RERR_ MXP | 0.039108 |
| 27 | RERR_KRW | 1.448813 | RERR_KRW | 0.576308 | RERR_ISR | 3.400326 | RERR_ ISR | 0.047478 |
| 28 | RERR_ ISR | 14.87059 | RERR_ ISR | 5.931519 | RERR_RUR | 5.089294 | RERR_ RUR | 0.053534 |

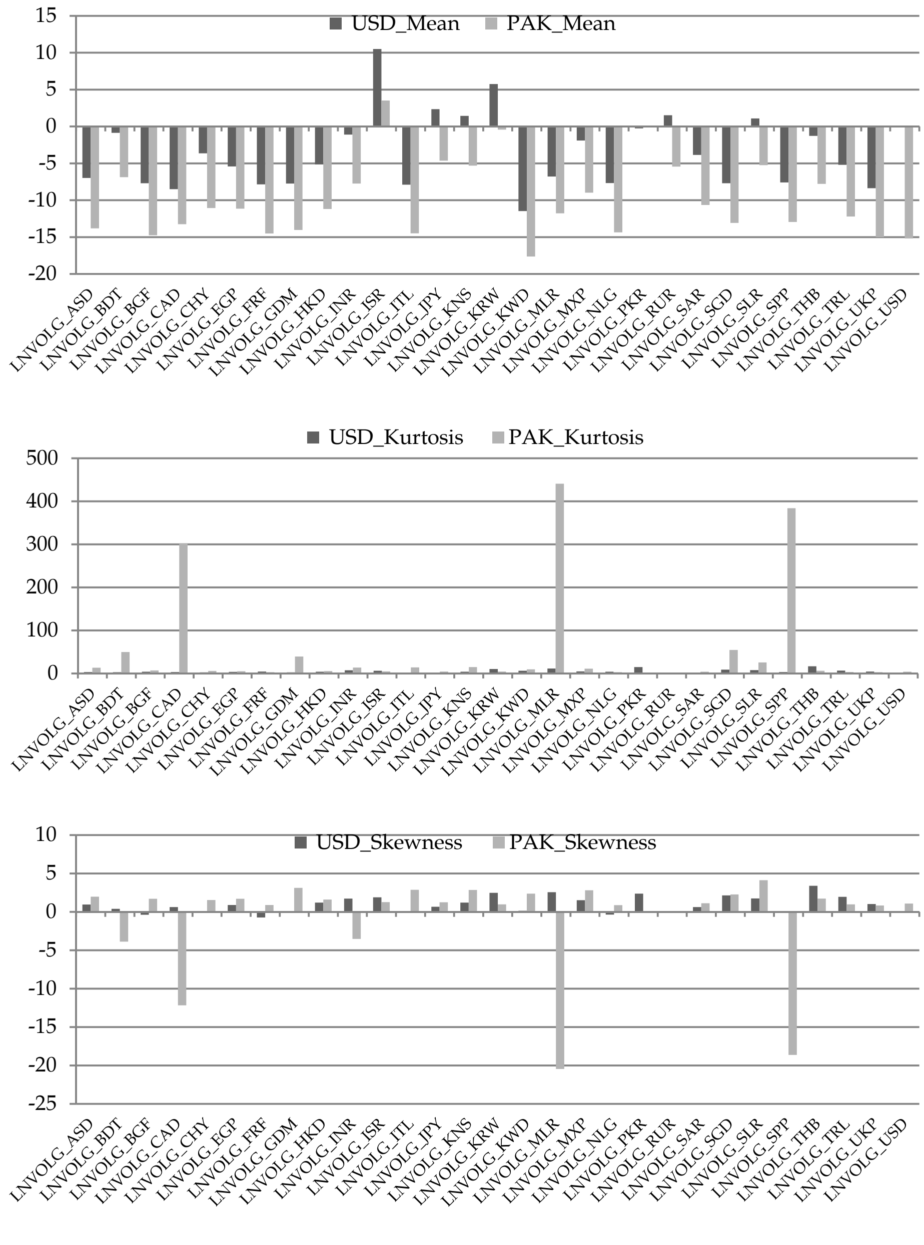
**Table A5: GARCH (1,1)-based volatility models: Ranking for one-step-ahead forecastabilities**

| Rank | Country | RMSE | Country | MAE | Country | MAPE | Country | TIC |
|---|---|---|---|---|---|---|---|---|
| 1 | RERD_ KWD | 0.003989 | RERD_ KWD | 0.002315 | RERD_HKD | 0.818198 | RERD_ CAD | 0.007135 |
| 2 | RERD_ UKP | 0.016892 | RERD_ UKP | 0.012388 | RERD_KWD | 0.967155 | RERD_ HKD | 0.007375 |
| 3 | RERD_ CAD | 0.017273 | RERD_ CAD | 0.012436 | RERD_CAD | 1.023763 | RERD_ SGD | 0.007597 |
| 4 | RERD_ ITL | 0.021542 | RERD_ ITL | 0.016327 | RERD_MLR | 1.060503 | RERD_ KWD | 0.007868 |
| 5 | RERD_ FRF | 0.021838 | RERD_ SGD | 0.016457 | RERD_THB | 1.106302 | RERD_ BDT | 0.008354 |
| 6 | RERD_ GDM | 0.022472 | RERD_ FRF | 0.016513 | RERD_SGD | 1.134477 | RERD_ MLR | 0.010716 |
| 7 | RERD_ SGD | 0.022487 | RERD_ GDM | 0.017398 | RERD_KRW | 1.276238 | RERD_ INR | 0.010868 |
| 8 | RERD_ BGF | 0.022766 | RERD_ BGF | 0.017440 | RERD_INR | 1.343092 | RERD_ PKR | 0.011705 |
| 9 | RERD_ SPP | 0.022992 | RERD_ SPP | 0.017540 | RERD_PKR | 1.416718 | RERD_ SPP | 0.011958 |
| 10 | RERD_ NLG | 0.023185 | RERD_ NLG | 0.018028 | RERD_SLR | 1.537641 | RERD_ ITL | 0.012264 |
| 11 | RERD_ASD | 0.035664 | RERD_ASD | 0.024312 | RERD_EGP | 1.661495 | RERD_ SLR | 0.012489 |
| 12 | RERD_ MLR | 0.059225 | RERD_ MLR | 0.028180 | RERD_ASD | 1.740194 | RERD_ UKP | 0.012643 |
| 13 | RERD_ TRL | 0.085540 | RERD_ TRL | 0.049123 | RERD_BDT | 1.818018 | RERD_ FRF | 0.012917 |
| 14 | RERD_ HKD | 0.103692 | RERD_ HKD | 0.057226 | RERD_KNS | 1.841720 | RERD_ASD | 0.012986 |
| 15 | RERD_ EGP | 0.174909 | RERD_ EGP | 0.062032 | RERD_ITL | 1.876958 | RERD_ NLG | 0.013066 |
| 16 | RERD_ SAR | 0.246322 | RERD_ SAR | 0.136703 | RERD_UKP | 1.880891 | RERD_ BGF | 0.013195 |
| 17 | RERD_ CHY | 0.265267 | RERD_ CHY | 0.187279 | RERD_SPP | 1.904525 | RERD_ THB | 0.013300 |
| 18 | RERD_ MXP | 0.713296 | RERD_ MXP | 0.359933 | RERD_FRF | 1.972002 | RERD_ GDM | 0.013327 |
| 19 | RERD_ INR | 0.777330 | RERD_ THB | 0.372437 | RERD_BGF | 2.046133 | RERD_ JPY | 0.013557 |
| 20 | RERD_ THB | 0.831448 | RERD_ INR | 0.456502 | RERD_NLG | 2.058306 | RERD_ KRW | 0.015561 |
| 21 | RERD_ BDT | 0.840653 | RERD_ PKR | 0.530364 | RERD_GDM | 2.083356 | RERD_ KNS | 0.015593 |
| 22 | RERD_ PKR | 1.045779 | RERD_ BDT | 0.560510 | RERD_JPY | 2.160038 | RERD_ CHY | 0.020849 |
| 23 | RERD_ SLR | 2.295653 | RERD_ SLR | 1.352817 | RERD_SAR | 2.185645 | RERD_ SAR | 0.021337 |
| 24 | RERD_ KNS | 2.683021 | RERD_ KNS | 1.568312 | RERD_ISR | 2.511726 | RERD_ EGP | 0.021644 |
| 25 | RERD_ JPY | 3.341192 | RERD_ JPY | 2.501477 | RERD_CHY | 2.837446 | RERD_ TRL | 0.024612 |
| 26 | RERD_ RUR | 15.26924 | RERD_ RUR | 3.689819 | RERD_TRL | 2.964899 | RERD_ MXP | 0.030326 |
| 27 | RERD_ KRW | 32.69792 | RERD_ KRW | 14.48374 | RERD_MXP | 3.006185 | RERD_ ISR | 0.050276 |
| 28 | RERD_ ISR | 728.8591 | RERD_ ISR | 224.0036 | RERD_RUR | 3.010868 | RERD_ RUR | 0.054797 |

# *Appendix 3*

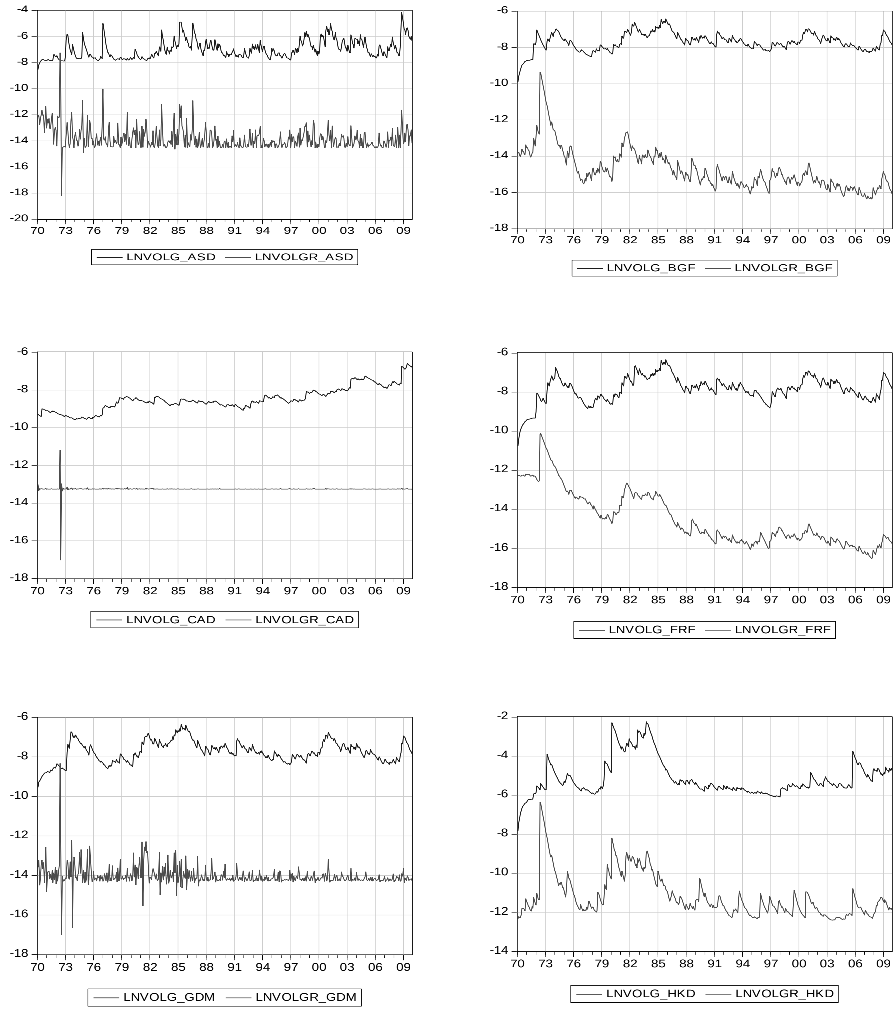
## Descriptive and Graphical results

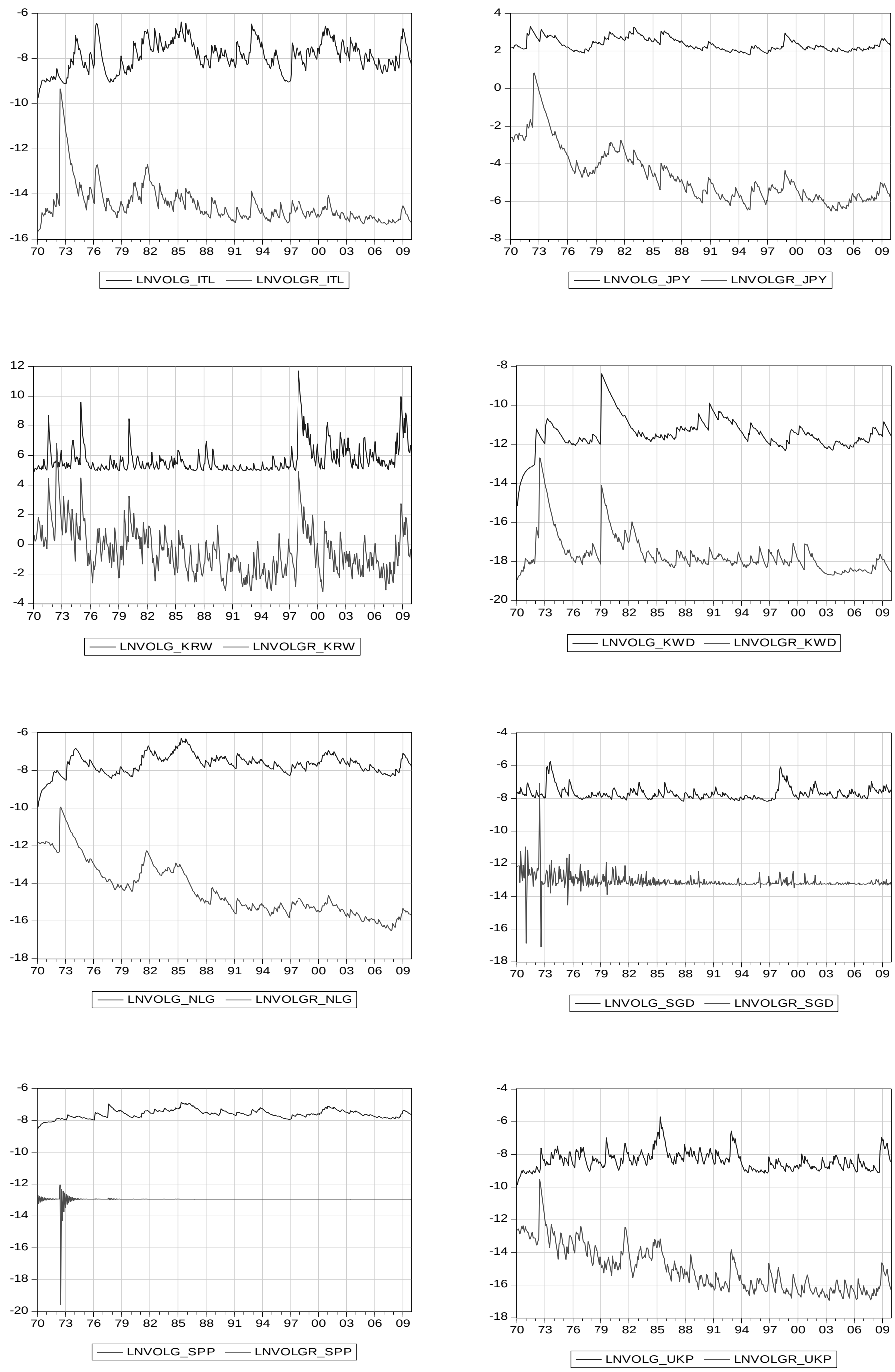
**Figure A1: Descriptive results: Comparison of two currency-based exchange rate volatilities**



# Figure A2: Monthly exchange rate volatility with GARCH (1,1) model

Developed Countries

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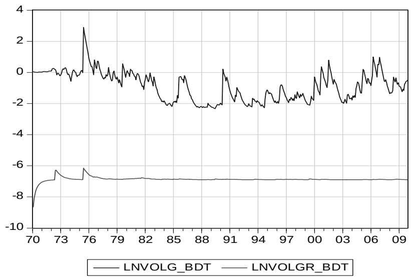
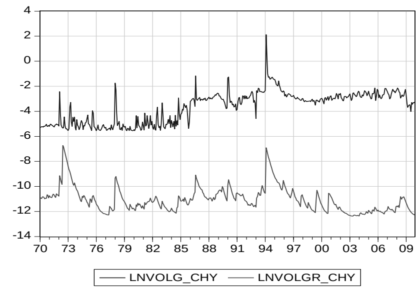
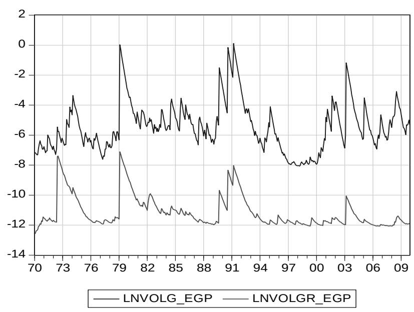
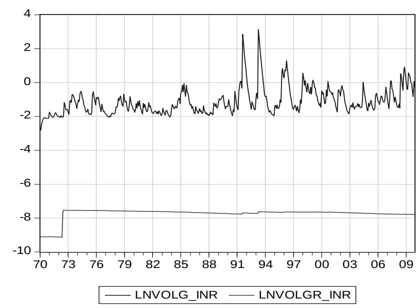
LNVOLG_KRW LNVOLGR_KRW
LNVOLG_KWD LNVOLGR_KWD
LNVOLG_NLG LNVOLGR_NLG
LNVOLG_SGD LNVOLGR_SGD
LNVOLG_SPP LNVOLGR_SPP
LNVOLG_UKP LNVOLGR_UKP

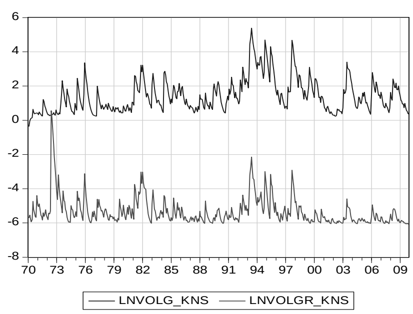
Developing Countries

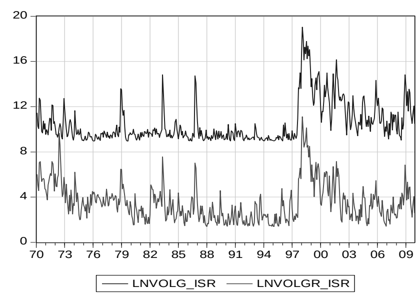


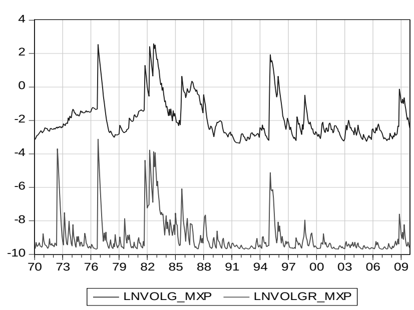



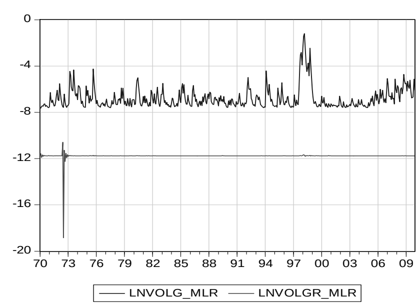



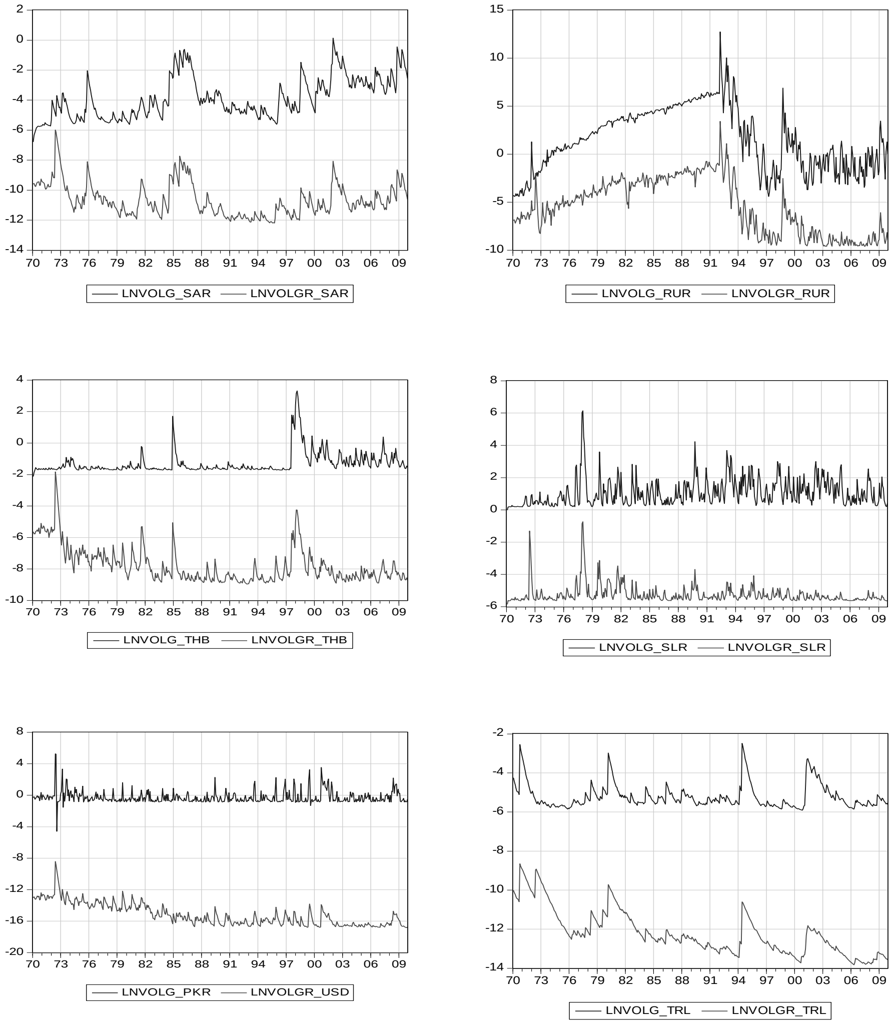






Note: In each graph, the upper line represents USD-based and the lower line PKR-based exchange rate volatilities, respectively. The x-axis shows time (monthly) from 1970/71 to 2009–12 and the y-axis shows the variance.

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# Interest Rate Pass-Through: Empirical Evidence from Pakistan

**Sheikh Khurram Fazal* and Muhammad Abdus Salam****

**Abstract**

*This article empirically examines the interest rate pass-through mechanism for Pakistan, using six-month treasury bills as a proxy for the policy rate (the exogenous variable) and the weighted average lending rate and weighted average deposit rate as endogenous variables representing the lending and deposit channels, respectively. We use data for a six-year period from June 2005 to May 2011, published by the central monetary authority in Pakistan. The widely accepted error correction mechanism is used to examine the short-run and long-run pass-through; a vector error correction mechanism impulse response function helps measure the short-run speed of the pass-through. We find that there is an incomplete pass-through in Pakistan for both the lending and deposit channels. The impact is greater on the lending channel than on the deposit channel in both the short and long run, while the adjustment speed is higher for the lending channel.*

**Keywords:** Interest rate pass-through, interest rate channel, transmission mechanism, monetary policy, Pakistan.

**JEL classification:** E43, E58.

## 1. Introduction

In recent years, central banks in developed and developing countries have tended to use monetary policy to promote growth and stabilize the economy. Parkin (2005, p. 483) and Stanlake and Grant (2000, p. 317) observe that monetary policy attempts to change the interest rate and quantity of money supply to bring about the desired changes in the economy; it is formulated by the country's central monetary authority. Arby and Hanif (2010) add that the role of the government and fiscal policy plays an important role, where monetary policy requires the support of fiscal policy to maintain its effectiveness and the autonomy of the central bank.

* Mitsubishi Corporation, Karachi.
** State Bank of Pakistan, Karachi.

### 1.1. Monetary Policy Tools

Monetary policy is considered one of the most influential tools used to affect growth, stabilize the price level, and control the economy's financial system. The State Bank of Pakistan (SBP) formulates and conducts the country's monetary policy, taking into consideration the current economic environment and future expectations about core economic variables such as output, inflation, and the exchange rate. The government, researchers, policymakers, and other stakeholders keep close watch over the SBP as it conducts monetary policy. The bank uses numerous monetary policy tools to stabilize and improve economic activity in Pakistan, some of which are listed below along with their rates:

- The discount rate (DR), policy rate, or reverse repo rate is the benchmark interest rate set by the SBP at which commercial banks and other depository institutions can borrow from the central bank on an overnight basis to meet their resource requirements. The DR in Pakistan is 14 percent (as on November 2010).
- Banks use the SBP's repo rate facility to park their excess cash reserves with the SBP on an overnight basis; it currently offers an 11 percent rate of return (as on November 2010).
- The minimum capital requirement (MCR) refers to the amount of net equity value of a bank's shareholders, after adjusting for losses (if any); this was PKR 7 billion as on December 2010, with PKR 8 billion to be maintained by December 2011 (State Bank of Pakistan, BSD Circular No. 07, 15 April 2009).
- Open market operations (OMOs) refer to the purchase or sale of government bonds or securities in the open market to inject or reduce excess money circulation in the commercial banks; in Pakistan, this is conducted by the SBP every fortnight.
- The cash reserve requirement (CRR) is the percentage of total demand deposits with less than a year's maturity that banks need to maintain on a weekly basis with the SBP, without any return being paid by the central bank. In Pakistan, it stands at 5 percent of the total deposits as of November 2008.
- The statutory liquidity reserve (SLR) requirement is the percentage of total demand deposits with less than a year's maturity that banks are

required to hold in government securities (excluding CRR); this currently stands at 19 percent for all banks in Pakistan as of June 2011. Earlier, Islamic banks were required to maintain 14 percent in SLR instead of the current 19 percent level.

- Letter of credit margin (LCM) is a proportionate value of importable goods that importers must deposit in their banks as a cash margin to avail credit from the bank to import cargo. This varies from commodity to commodity in Pakistan.
- The export refinancing rate (ERR) is the rate at which an exporter in Pakistan can borrow from the commercial banks at a subsidized rate. It is linked to the last three auctions' weighted average yields of six-month treasury bills (TB6M) against future export proceeds; is the ERR currently hovers around 10 percent.
- Moral suasion usually refers to cases where the central bank persuades commercial banks to lend smaller funds to borrowers.

The classical tool for achieving macroeconomic goals in monetary theory is the policy rate or DR, which is determined by the monetary authority's board of governors, based on macroeconomic activity and the health of the economy. The DR is highly instrumental in influencing various market rates, which in turn affect the factors of economic activity directly or indirectly with a certain time lag, depending on the size of shocks, the prevailing economic environment, retail market or banking industry competition, the risk appetite of creditors and depositors, and the degree of economic openness.

Stanlake and Grant (2000, p. 319) define monetary policy transmission as the passing of policy shocks to economic variables and the time taken by these shocks to affect economic variables such as output and price level to improve the monetary system's health in the economy. In recent studies, more emphasis has been given to the effect of short-term interest rates, with the core objective of stabilizing real output, inflation, the exchange rate, unemployment, and other economic variables.

### *1.2. Research Problem*

According to the literature, most central banks have identified a positive significant relationship between the DR and market interest rates, especially for the deposit channel of interest rate pass-through (the time and magnitude of impact on financial market retail rates, namely deposit and lending rates, in response to a change in the policy rate). In Pakistan, the central bank has effected several structural changes to improve the effectiveness of its monetary policy transmission mechanism over the last five years. This study aims to examine empirically the impact of policy shocks on the market retail lending and deposit rates in Pakistan.

### *1.3. Research Objective*

Our main objective is to empirically examine if there is a significant impact on the retail lending and deposit rates in response to a policy rate decision or shock, along with its magnitude in the short and long run and the speed of pass-through from a policy shock to retail rates in the short run.

### *1.4. Importance of the Study*

This quantitative research will help understand whether the Keynesian perspective on the key interest rate pass-through mechanism in Pakistan is effective for market lending and deposit rates, i.e., how significantly the response to a decision on the policy rate proxy (TB6M) is transferred to the market lending and deposit rates. There is evidence of a higher pass-through into the lending channel than the deposit channel. The speed of the pass-through is also greater for market lending rates in the short and long run compared to market deposit rates.

The remainder of the article is organized as follows. Section 2 reviews the relevant literature, and is followed by a theoretical and conceptual framework in Section 3. Section 4 details the research methodology used. Section 5 presents and discusses the data and estimation results. Sections 6 and 7 provide a conclusion and policy recommendations, respectively.

## 2. Literature Review

Monetary authorities across the world have striven to enhance the effectiveness of monetary policy and the responsiveness of economic variables to policy decisions, especially after the global financial crisis that affected both developed and developing economies. Mishkin (1996) describes the different monetary policy channels, with an emphasis on the interest rate, exchange rate, equity price, and bank lending channels. Takim (2011) states that the interest rate channel is based on the Keynesian IS-LM perspective of monetary transmission mechanisms. Emphasizing the traditional interest rate channel, Mishkin (1996) explains that an expansionary policy decreases the nominal and real interest rates, in turn decreasing the cost of capital, increasing aggregate demand, and increasing the level of output.

Other channels identified include the expectations channel, which is considered to be closely associated with the interest rate channel. Dabla-Norris and Floerkemeier (2006) and Takim (2011) explain that the expectations channel relies on the central bank's inflation targeting regime by changing key interest rates; this directs economic agents' future outlook on the economy. Dabla-Norris and Floerkemeier (2006) stress that, if the expectations channel is effective, it signals the higher credibility of the central bank. Additionally, Takim (2011) argues that the interest rate channel holds on the basis that inflation expectations do not change in the economy. Horváth and Maino (2006) examine the economy of Belarus and confirm that the expectations channel seems to have played an important role in curbing the price level, based on its strong influence over economic activity, which allows it to act as a nominal anchor.

Bernanke and Blinder (1992) empirically examine the US economy using a vector autoregressive (VAR) impulse response function (IRF). They find that the fund rate is a good measure of monetary policy shocks, where loans respond comparatively slowly to deposits, as the rate is fixed for the contracted period of the loan.

Hofmann and Mizen (2004) investigate the base rate pass-though to retail rates in the UK, using 17 years' data on several deposit and mortgage rates. They find that there is a complete pass-through in the long run from the policy rate to the DR as compared to an incomplete pass-through to the mortgage rate. In a study on interest-based deposit and credit products, Fuertes, Heffernan, and Kalotychou (2008) present similar findings for the UK. They use a conventional nonlinear and linear error correction mechanism (ECM) to determine the adjustment speed of various UK bank retail rates, and find that the change in speed differs in proportion to the magnitude of a policy shock. They also find that deposit rates tend to adjust faster during monetary expansion, while mortgage rates tend to adjust more rapidly during monetary contraction.

Examining Turkey's economy, Aydin (2010) investigates the lending side and finds that the pass-through is higher for all types of loans. Consumer lending rates tend to be of a higher magnitude than corporate lending rates, and the pass-through in cash and automobile loans is also completed after a credit boom. Using an ECM to analyze Romania's interest rate pass-through, Tieman (2004) finds that deposit rates tend to respond quicker than lending rates, with the pass-through increasing gradually over time. In relation to Armenia's economy, Dabla-Norris and Floerkemeier (2006) find that, on average, lending rates respond instantaneously to a change in the policy rate, although the interest rate elasticity is expected to be low due to less banking competition in the country.

Examining Jordan's economy Poddar, Sab, and Khachatryan (2006) apply a VAR model to the real three-month certificate of deposit rate as a benchmark of policy shocks to determine the real retail rate's reaction within the same month. They find that deposit rates react at a higher magnitude of 92 bps, compared to 74 bps for lending rates. Al-Mashat and Billmeier (2007) find that the interest rate channel remains weak in Egypt because of the higher interest spread of the banking industry, due mainly to low banking competition in the country's financial system.

Generally, researchers have found that, once the central bank changes the policy rate, it is reflected in the short-term market rate with a certain time lag depending on the prevailing economic environment. Qayyum, Khan, and Khawaja (2005) examine the interest rate pass-through for Pakistan's economy, applying the autoregressive distributed lag (ARDL) econometric technique to the TB6M yield rate as a benchmark of policy shocks. They find that complete pass-through occurs for the call money (CM) rate, with a mere 18 bps impact on the savings deposit (SD) rate in six months, but there is no pass-through in the six-month SD rate and weighted average lending rate (WALR) during the first six months of a policy shock. However, their study is limited in terms of methodology, analysis, and reporting; specifically, it uses monthly data for the TB6M and CM rates and six-monthly data for the other variables. This reduces the amount of variation in the data and information contained theirin, and makes it difficult to generalize the findings. Although they claim that high-frequency data should be used for such analysis, they have used two different data series with low-frequency data.

## 3. Theoretical Framework

Based on Mishkin (1996) and Takim (2011), we deduce that a contractionary monetary policy increases the short-term nominal and real interest rates, raises the lending rates to the private sector, leads to a higher cost of capital for firms, and reduces their demand for investment spending. This, in turn, reduces aggregate demand in the economy with the target of curbing inflation, ceteris paribus. This is expressed as:

M ↓ → DR ↑ → ↑ L → ↑ CC → ↓ IS → ↓ AD → ↓ INF

where M↓ indicates the contractionary monetary policy, DR↑ indicates an increase in the DR, ↑L indicates an increase in the nominal and real lending rates, ↑CC shows the increase in the cost of capital, ↓IS indicates a decrease in investment spending demand, ↓AD represents the decrease in aggregate demand in the economy, and ↓INF indicates a decline in inflation.

Mishkin (1996), Agha, Ahmed, Mubarik, and Shah (2005), and Takim (2011) argue that a contractionary monetary policy simultaneously creates incentive for banks and financial intermediaries to earn higher returns by investing more in virtually risk-free government securities rather than catering to medium- to high-risk private sector credit demand. This increases their demand for deposits, such that they offer a higher deposit return rate, giving depositors incentive to enhance their banking deposits by delaying consumption spending to earn a higher return. Ultimately, this reduces aggregate demand in the economy with the main target of curbing inflation, ceteris paribus:

M ↓ → DR ↑ → ↑ D → ↑DEP → ↓ AD → ↓ INF

where M↓ indicates the contractionary monetary policy, DR↑ indicates an increase in the DR, ↑D represents an increase in the nominal and real deposit rates offered to depositors, ↑DEP indicates an increase in the quantum of financial deposits, ↓AD represents a decrease in aggregate demand in the economy, and ↓INF indicates a decline in inflation.

### *3.1. Conceptual Framework*

Qayyum et al. (2005), Aydin (2010), and Poddar et al. (2006) stress that a contractionary monetary policy that increases the policy rate (reflected in the t-bill yield) also affects the market lending rate, thereafter affecting the demand for investment credit, investment spending, and output, ceteris paribus:

$$M \downarrow \rightarrow DR \uparrow \rightarrow TB \uparrow \rightarrow \uparrow MLR$$

where M↓ indicates the contractionary monetary policy, DR↑ indicates an increase in the DR, TB↑ represents an increase in the t-bill yield, and ↑MLR indicates an increase in market lending rates.

Tieman (2004), Poddar et al. (2006), and Fuertes et al. (2008) explain that a contractionary monetary policy gives banks and financial intermediaries incentive to earn a higher (almost) no-risk return on investment, thereby increasing their demand for public deposits. This implies that they will offer depositors a higher deposit return, thereby affecting consumption demand and output in the economy, ceteris paribus:

$$M \downarrow \rightarrow DR \uparrow \rightarrow TB \uparrow \rightarrow \uparrow MDR$$

where M↓ indicates the contractionary monetary policy, DR↑ indicates an increase in the DR, TB↑ represents an increase in the t-bill yield, and ↑MDR represents an increase in the market deposit rates offered to depositors.

### *3.2. Hypotheses*

Our two hypotheses are:

H1: The policy rate does not affect market lending rates in Pakistan.

H2: The policy rate does not affect market deposit rates in Pakistan.

The first hypothesis (H1) determines whether the policy rate has a significant impact on the incremental and outstanding WALR. The second hypothesis (H2) tests whether the policy rate has a significant impact on the incremental and outstanding weighted average deposit rate (WADR). Based on the theoretical and conceptual frameworks we use, the policy rate should have a significant impact on the market retail rates—implying that we can reject these hypotheses—and the relationship should be positive for all four market retail rates being considered.

## 4. Research Methodology

This is a quantitative study and in examining the interest rate pass-through under the recent contractionary monetary policy regime, we use secondary data published by the SBP for our empirical analysis, estimations, and model selection. The main reason for selecting the contractionary monetary policy stance is to determine whether the current policy-based interest rate shocks are reflected in the market retail rates. Time-series data on incremental and outstanding market retail rates is available for the period January 2004 onward, so the earlier period is not included. Additionally, the SBP's expansionary policy stance rapidly changed into a contractionary policy stance from late 2004 and early 2005; such transitional and highly volatile interest rate values tend to affect estimations and results.

### *4.1. Choice of Variables*

We attempt to empirically explain the phenomenon of interest rate pass-through, using the TB6M (a proxy for the policy rate or DR) as an exogenous variable. This is mainly because the monetary policy was announced twice a year during the earlier years, implying that the DR would become a discrete variable until a change in it was announced. This can affect the estimation results due to the change in the frequency of variables in the model. Additionally, the market rates remain dynamic while there is no change in the DR, making it likely that we would lose important information prevailing in the financial market. Therefore, it becomes important to match the variables' frequency and introduce variability to incorporate financial market information impacts on interest rates.

A number of studies prefer using the interest rate policy proxy. Bernanke and Blinder (1992) find that the federal fund rate is a good proxy for the policy rate, while Agha et al. (2005), Qayyum et al. (2005), and Javid and Munir (2010) use the TB6M as a proxy for the DR in examining the monetary policy transmission mechanism of Pakistan's economy. We follow suit and use the TB6M as a proxy for the DR because the TB6M weighted average yield is derived by the SBP itself while carrying out OMOs fortnightly, mainly to support the government in fiscal deficit financing, to limit government borrowing from the central bank, and to reduce the excess liquidity available in the financial market by selling government bonds in which banks are the predominant participants. Additionally, since OMOs are conducted fortnightly, the formulation of the TB6M monthly series requires averaging two values every month in most cases.

Based on the theory, the lending rate is the markup paid by borrowers to the bank (lender) for the credit provided, while the DR is the return paid by banks to their depositors. The endogenous variables for the market lending rate include the WALR gross disbursements[1] (incremental loans) and WALR total outstanding loans by all banks, including zero-markup loans. For the market deposit rates, we use the WADR fresh deposits[2] (incremental deposits) and WADR total outstanding deposits by all banks, including zero-markup deposits.

The formula for calculating the weighted average rate is:

$$\text{Weighted average rate} = \sum (\text{rate x amount}) \div \sum (\text{amount})$$

### *4.2. Data*

Our data on the variables above spans six years, comprising 72 observations from June 2005 to May 2011, published by the SBP and available online. The literature varies on the number of observations to be used in such an analysis but requires the data to be asymptotic (technically, constituting a large sample). Our observations are considered asymptotic based on Gujarati and Sangeetha's (2007, p. 485) criterion that data comprising 50 or more observations is considered reasonably large. Selvanathan, Selvanathan, Keller, and Warrack (2004, p. 772) state that the difference between the R-squared and adjusted R-squared terms should be a minimum, giving the example of a difference of 0.037 as being moderately good. We use a higher benchmark difference—a 0.010 difference that is appropriate to the sample size and is well within the benchmark. Hence, our sample size is reasonable for empirical analysis purposes.

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[1] Gross disbursements are incremental disbursements rolled over or repriced either in Pakistan rupees or in foreign currencies during the month. For running finance, the maximum credit facility availed at any point during the month by the borrower is included.

[2] Fresh deposits are newly opened accounts and rolled-over or repriced deposits during the month.

*Adjustments in Data*

Data on the market lending and deposit rates is available on a monthly basis, compared to data on the TB6M, which is available more frequently, being dependant on the auction conducted by the SBP every 14th day. In order to ensure homogeneity and balance among the variables' frequency, we adjust the TB6M data by taking the simple average of the TB6M weighted average yields in the month they were conducted. Thus, if there were two OMOs in a month, then the sum of yields is divided by 2 to calculate the simple average yield or the yield rate for the month or, as the case may be, depending on the number of OMOs conducted in a month.

### *4.3. Model Selection*

Based on an understanding of the literature and the simplicity of the empirical analysis, we use the least squares method. After examining the classical linear regression model (CLRM) assumptions, where CLRM-estimated parameters provide the long-run magnitude of the interest rate pass-through, we determine the presence of a unit root in the individual time series using the augmented Dickey-Fuller (ADF) test. This indicates that the ECM and vector error correction mechanism (VECM) models should be applied to empirically examine the short-run dynamics.

Prior to this, a two-step Engle-Granger test (EG) (see Engle & Granger, 1987) is applied to confirm the cointegration between the variables of the equation and the long-run relationship between the model's variables. We use the ECM and VECM IRF with an errors-reduced form of Cholesky decomposition (see Sims, 1980) to estimate the short-run magnitude and speed of the pass-through.

## 5. Data Analysis and Estimation

The secondary data on the variables is used to estimate the CLRM. Initially, we test the CLRM assumptions based on the following econometric equations for the lending and deposit channels:

*Lending* $$WALR = \beta_1 + \beta_2 TB6M + ul_t \quad (1)$$

*Deposit* $$WADR = \beta_3 + \beta_4 TB6M + ud_t \quad (2)$$

where the $\beta$ terms are the estimated parameters, and $ul_t$ and $ud_t$ are the error terms from the lending and deposit channel equations, respectively. The results are summarized in Table 1, and provide the basis for estimating the long-run parameters of the CLRM.

**Table 1: Results of CLRM estimation**

| | Incremental WALR | Outstanding WALR | Incremental WADR | Outstanding WADR |
|---|---|---|---|---|
| Intercept | 2.6169 | 4.0960 | -0.7471 | -2.6278 |
| t-statistic | 8.4377 | 12.6550 | -1.8934 | -8.6345 |
| (Prob.) | (0.0000) | (0.0000) | (0.0624) | (0.0000) |
| TB6M | 0.8868 | 0.7476 | 0.6566 | 0.6878 |
| t-statistic | 31.2423 | 25.2380 | 18.1835 | 24.6923 |
| (Prob.) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| R-squared | 0.9330 | 0.9009 | 0.8252 | 0.8970 |
| Adj. R-squared | 0.9321 | 0.8995 | 0.8227 | 0.8955 |
| Durbin-Watson | 0.8230 | 0.3701 | 0.5463 | 0.2934 |

***Source:*** Authors' calculations.

The different tests applied confirm all the CLRM assumptions, with the exception of the no-autocorrelation assumption, which is violated in all four regressions. There is positive autocorrelation in the regression results above, which is evident from the Durbin-Watson statistic. Generating a correlogram for each endogenous variable reconfirms the autoregression function at the first lag. Gujarati and Sangeetha (2007, pp. 822–827) do not, however, take into consideration the impact of autocorrelation, and identify the estimated (static) parameter as the long-run equilibrium relation. Additionally, the normality-of-errors assumption required for certain econometric tests is not fulfilled for the incremental WALR regression equation. The results are summarized in Table 2.

**Table 2: Jarque-Bera (J-B) test (H0: normal distribution of errors)**

| | Incremental WALR | Outstanding WALR | Incremental WADR | Outstanding WADR |
|---|---|---|---|---|
| J-B statistic | 15.1705 | 3.2451 | 1.1313 | 0.4447 |
| (Prob.) | (0.0005) | (0.1973) | (0.5679) | (0.8006) |

***Source:*** Authors' calculations.

The nonnormality of errors for the incremental WALR regression is not considered to have an impact on our analysis because the data is considered to be asymptotic. As Brooks (2008, p. 164) points out, for sufficiently large samples, the normality-of-errors assumption is virtually inconsequential based on the central limit theorem. This is confirmed by Gujarati and Sangeetha (2007, p. 346) with the additional comment that it is vital to assume fixed exogenous variable values in repeated trials and homoskedasticity (error variance to be constant).

The ADF[3] test is then applied to test for the presence of a unit root, determining the stationarity of each individual series in levels. The results confirm that all the variables are nonstationary in levels but are stationary in the first difference or *I(1)* (see Table 3).

**Table 3: Results of ADF test (H0: unit root)**

| | **TB6M** | **Incremental WALR** | **Outstanding WALR** | **Incremental WADR** | **Outstanding WADR** |
|---|---|---|---|---|---|
| In level: ADF statistic | -0.9007 | -1.2317 | -1.1008 | -1.9023 | -1.6885 |
| (Prob.) | (0.7826) | (0.6561) | (0.7112) | (0.3295) | (0.4326) |
| In first difference: ADF statistic | -8.9680 | -3.5656 | -3.7396 | -10.5740 | -5.7210 |
| (Prob.) | (0.0000) | (0.0090) | (0.0054) | (0.0001) | (0.0000) |

***Source:*** Authors' calculations.

Next, the errors ($ul_t$ and $ud_t$) generated from equations (1) and (2) are tested separately using the ADF. The results show that all four regression errors are stationary in levels, confirming the combined integration. Table 4 summarizes these findings.

**Table 4: Augmented Dickey-Fuller (ADF) Test (H0: Unit Root)**

| | **Incremental** $ul_t$ | **Outstanding** $ul_t$ | **Incremental** $ud_t$ | **Outstanding** $ud_t$ |
|---|---|---|---|---|
| **At Level: ADF Statistic** | **- 5.0402** | **- 3.7251** | **- 2.6646** | **- 2.6587** |
| (Prob.) | (0.0000) | (0.0003) | (0.0083) | (0.0085) |

***Source:*** Authors Calculation

[3] The Dickey Fuller (DF) test is not used to test for a unit root because it is not powerful enough to overcome the violation of the no-autocorrelation assumption. See Dickey and Fuller (1979) for details.

The EG test is carried out to confirm the cointegration between the variables of each equation. The first step is to run the CLRM and estimate the error (residual) series $ul_t$ and $ud_t$ for the lending and deposit channels, respectively. These series have already been estimated in equations (1) and (2). The second step is to run the following auxiliary regressions:

*Lending* $$\Delta ul_t = \tau_1 ul_{t-1} + \varepsilon l_t \quad (3)$$

*Deposit* $$\Delta ud_t = \tau_2 ud_{t-1} + \varepsilon d_t \quad (4)$$

where Δ represents the first difference between the error values calculated from equations (1) and (2), the $\tau$ terms are the computed t-statistic values calculated using the EG test, and $\varepsilon l_t$ and $\varepsilon d_t$ are the residuals from the auxiliary regressions of the lending and deposit channels, respectively. The results of the second step of the EG test are summarized in Table 5.

**Table 5: Results of EG test (second-step estimates)**

| | Incremental WALR | Outstanding WALR | Incremental WADR | Outstanding WADR |
|---|---|---|---|---|
| $u_{t-1}$ | -0.4700 | -0.2493 | -0.2903 | -0.1661 |
| t-statistic | -5.0402 | -3.7251 | -3.5400 | -2.6587 |
| EG critical ( $\tau$ = t) value at 1% = -2.5899 | | | | |

***Source:*** Authors' calculations.

The computed values are negative (as mentioned in the literature) and significant relative to the 1 percent critical value of -2.5899. The regressions in equations (1) and (2) are, therefore, cointegrated, confirming that the results are not spurious. The regression coefficients or $\beta$ terms estimated from equations (1) and (2) can be considered long-run parameters and, hence, there is equilibrium at least in the long run.

Having confirmed the cointegration, we apply an ECM to estimate the short-run parameters, using the following regressions:

*Lending* $$\Delta WALR = \psi_1 + \psi_2 \Delta TB6M + \psi_3 ul_{t-1} + e_{1t} \quad (5)$$

*Deposit* $$\Delta WADR = \psi_4 + \psi_5 \Delta TB6M + \psi_6 ud_{t-1} + e_{2t} \quad (6)$$

where Δ represents the first difference between the current and lagged values of *WALR*, *WADR*, and *TB6M*; the $\psi$ terms are the slope coefficients; $ul_{t-1}$ and $ud_{t-1}$ are the first-lag error values estimated from equations (1) and (2), respectively; and $e_{1t}$ and $e_{2t}$ are the residuals from equations (5) and (6), respectively.

Table 6 gives the empirical parameter estimates of the ECM.

**Table 6: ECM estimation**

| | **Incremental WALR** | **Outstanding WALR** | **Incremental WADR** | **Outstanding WADR** |
|---|---|---|---|---|
| Intercept | 0.0571 | 0.0633 | 0.0353 | 0.0447 |
| t-statistic | 1.4663 | 4.1455 | 0.7115 | 2.8795 |
| (Prob.) | (0.1472) | (0.0001) | (0.4792) | (0.0053) |
| ΔTB6M | 0.3727 | 0.1508 | 0.3058 | 0.1874 |
| t-statistic | 4.1367 | 4.3507 | 2.6199 | 5.3188 |
| (Prob.) | (0.0001) | (0.0000) | (0.0108) | (0.0000) |
| $u_{t-1}$ | -0.3655 | -0.1818 | -0.2195 | -0.1064 |
| t-statistic | -4.5761 | -6.1487 | -2.6884 | -3.3136 |
| (Prob.) | (0.0000) | (0.0000) | (0.0090) | (0.0015) |
| R-squared | 0.3130 | 0.4260 | 0.1384 | 0.3413 |
| Adj. R-squared | 0.2927 | 0.4092 | 0.1131 | 0.3220 |
| Durbin-Watson | 1.7269 | 0.6565 | 2.3956 | 1.4187 |

***Source:*** Authors' calculations.

The above findings reveal that the errors are significant even at a 1 percent level of significance, thus reconfirming the use of the estimated ΔTB6M parameters as short-run pass-through estimates. The findings indicate the impact on the endogenous variables in the short run based on a 100 bps (1 percent) increase in the policy rate proxy or policy shock.

To confirm whether there is a complete pass-through in market retail rates due to a policy shock in the long run, the estimated parameters ( $\beta$ terms) of market lending and deposit rates from equations (1) and (2), respectively, are tested using the Wald coefficient test (Table 7).

**Table 7: Results of Wald test (H0: $\beta$ = 1)**

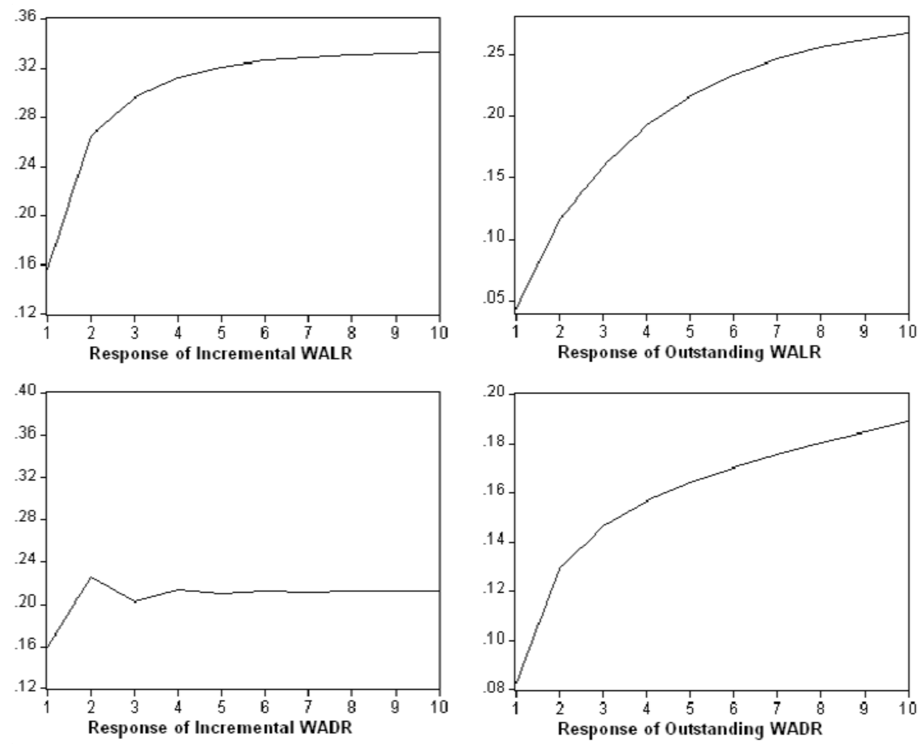
| | Incremental WALR | Outstanding WALR | Incremental WADR | Outstanding WADR |
|---|---|---|---|---|
| F-statistic | 15.8847 | 72.5549 | 90.3648 | 125.5990 |
| (Prob.) | (0.0002) | (0.0000) | (0.0000) | (0.0000) |

***Source:*** Authors' calculations.

The Wald coefficient test's null hypothesis implies complete interest rate pass-through (H0: $\beta$ = 1) to market retail rates in the long run. The results reveal that the estimated parameters in Table 1 are, on average, not equal to 1. Hence, complete pass-through from a policy shock to Pakistan's financial system in the long run does not hold for both the lending and deposit channels, as indicated by the probability values in Table 7. We therefore reject the null hypothesis of complete pass-through to market retail rates. This poses several questions for future research concerning the applicability of the interest rate channel in the context of Pakistan, the reason(s) for incomplete pass-through, and the financial markets' competition level and practices, etc.

Finally, we use the VECM IRF to determine the speed of the short-run pass-through. Figure 1 shows its estimated duration and the variations in the endogenous variables due to a policy rate shock of 100 bps (1 percent).

**Figure 1: Impulse response functions**




***Source:*** Authors' calculations.

In the short run, on average, a 100 bps increase in the TB6M leads to a 33 bps (approximate) increase in the incremental WALR over six months. Similarly, a 100 bps increase in the TB6M in the short run leads to an average 25 bps (approximate) increase in the outstanding WALR over seven months from the time of the policy shock. In terms of the deposit channel, on average, there is a 21 bps (approximate) increase in the incremental WADR over four months, which is thereafter consolidated at this level in the short run. A 100 bps policy shock leads, on average, to a 17 bps (approximate) increase in the outstanding WADR over six months.

### *Inferences and Discussion*

We have found evidence that, in the long run, the incremental WALR increases by 89 bps and the outstanding WALR by 75 bps (see Table 1) on average due to a 100 bps increase in the policy rate proxy. In the short run, the incremental WALR increases by 37 bps on average compared to a

15 bps increase in the outstanding WALR—this is as expected because the outstanding WALR includes previous-period loans and investments on which the rate of return is fixed either till the maturity of the loan contract or the particular time agreed in the loan contract.[4] The speed of pass-through in the short run for the incremental WALR with an increase of 33 bps is six months, while an increase of 25 bps takes seven months for the outstanding WALR. It is interesting to note that the ECM's short-run parameter for the outstanding WALR is 15 bps compared to 25 bps yielded by the VECM, which is a robust model.

In economies where fiscal indiscipline is high, as in Pakistan's case, the pass-through for lending rates is incomplete mainly because banks are determined to earn higher returns by investing in (almost) no-risk sovereign bonds and securities, rather than lending to the risky private sector and charging borrowers a risk premium (see Faini, 2005, in relation to the euro area, and Akyurek, Kutan, & Yilmazkuday, 2011, in the context of the Turkish economy).

Additionally, when government borrowings exceed market expectations, increasing the associated risk, there is an insignificant difference in interest rate yields from government financing and lending to other financial institutions. This is evident in the difference between the TB6M and KIBOR[5] six-month rates, which in June 2011 stood at a meager 5 bps.[6] The rate of return on government securities remains fixed throughout the term of the bond or security, and despite a change in the benchmark interest rate and adjustment in the price of the security by secondary market forces according to the policy rate change, lending rates in the long run tend to have a smaller impact associated with policy shocks. This is a possible reason for the incomplete pass-through in the lending channel.

With reference to the deposit channel of the pass-through, the incremental WADR increases by 66 bps compared to the outstanding WADR, which increases by 69 bps on average in the long run following a 100 bps increase in the policy rate proxy. This is unexpected and may be

[4] Several lending products in Pakistan are based on flexible interest rates that are revised annually, biannually, or quarterly.

[5] The KIBOR is the Karachi interbank offered rate—the reference rate for the corporate lending of funds between financial institutions in Pakistan.

[6] The difference is calculated using the TB6M OMO conducted by the SBP on 29 June, i.e., a yield of 13.7283 percent and the corresponding KIBOR of 13.78 percent on the same date.

due to delayed consumption decisions in the long run by parties who have invested in bank deposits; it is unlikely in the short run due to precautionary consumption demand, but needs to be studied further in detail. In the short run, the incremental WADR increases by 31 bps compared to a 19 bps increase in the outstanding WADR, which is as expected. The speed of the pass-through in the short run is four months for the incremental WADR, yielding an increase of 21 bps, while an increase of 17 bps occurs over six months in the case of the outstanding WADR.

Due to the SBP's higher MCR requirement to safeguard depositors' funds with banks—which seems appropriate given the current financial turmoil—the banking industry has experienced several mergers and acquisitions. This has resulted in lower competition within the banking system and has induced banks not to pass on the increase in policy rate to their depositors. At the same time, depositors concerned about the financial health of the banks are less willing to place their deposits with smaller banks (who are in need of fresh deposits) at a higher deposit rate due to the higher associated risk. This pushes the WADR downward, although the larger banks may still offer a lower or minimum deposit rate of 5 percent on savings deposits as stipulated by the SBP.

Interestingly, there is an opportunity for scheduled banks to raise public deposits at a rate closer to the incremental WADR and park these at the SBP's repo rate of 11 percent. These earn an overnight marginal return, and as of May 2011 yield easy earnings at a 3.55 percent rate of return on carrying out such transactions. Additionally, the spread of the banking sector stands at high levels of 6.76 percent between the incremental WALR and WADR, and 7.65 percent on the outstanding WALR and WADR as on May 2011, again indicating the inefficiency and low degree of competition in Pakistan's banking sector.

Theoretically, government borrowings need to be curtailed and the fiscal and monetary policies' stance should complement one another. Significant government borrowings may lead to supply-push inflation in the long run, when the private sector is unwilling to invest at a higher cost of capital, which in turn results in a lower level of output compared to aggregate demand. Although this point remains beyond the scope of this paper, it is vital that future empirical investigations examine the impact of government borrowings on market rates and the economy itself.

## 6. Conclusion

The interest rate pass-through from a policy shock to the market lending and deposit rates is incomplete in Pakistan, even in the long run. There is evidence that changes in the policy rate have a significant impact on the market lending and deposit rates. Although the pass-through on the lending side is reasonably higher (close to complete) than on the deposit side, it remains incomplete for both lending and deposit channels. The higher pass-through to lending and the lower pass-though to the deposit channel both lead to a higher interest rate spread for the country's banking industry. This may reduce the effectiveness of the monetary policy stance and conduct, and lead to lower banking competition. The speed of the pass-through is also higher on the lending side both in the short and long run.

Based on the analysis above, we can reject the null hypotheses (H1 and H2) as policy rate shocks are seen to have a positive significant impact on market lending and deposit rates, implying that the interest rate pass-through is active in Pakistan.

### *Limitations and Road Ahead*

The limitations of this study point to areas for further empirical investigation to generate improved policy implications:

- Our empirical analysis is based on a contractionary policy stance. Adding data related to an expansionary monetary policy would provide a comparative analysis of the impact of policy rate shocks on market retail rates.
- A structural shock by the SBP (BPRD Circular No. 07 of 2008) caused by placing a minimum deposit return of 5 percent on all savings cannot be taken into account by the ECM, as the second-step differencing of the dummy variable will result in zero values. However, a longer time series could be used to analyze the data separately in two parts, once sufficient observations are available.
- Our findings are based on the current contractionary policy stance, which might not support accurate policy formulation if the policy stance were to change, or if it were affected by a policy decision or other economic factors with a significant impact on the interest rate pass-through.

- Studying the impact of government borrowings from the central bank and financial system would support the preparation of a better, more influential monetary policy in Pakistan.

## 7. Policy Recommendations

Based on our analysis, we present the following recommendations and avenues for further research on improving the financial market's effectiveness and interest rate pass-through in Pakistan.

It is important to ensure that the MCR level will safeguard public deposits. At the same time, some policy measure is required to bring the interest rate spread of the banking system around to the regional level, to pass on policy shocks to market retail rates, which could improve the effectiveness of monetary policy conduct in Pakistan. One possible measure could be the use of a flexible minimum deposit rate directly linked to the key policy rate or DR.

It is also important to highlight once again that our analysis and policy recommendations apply only to a contractionary monetary policy—once there is a structural change in the economic environment of Pakistan, it may be necessary to re-examine the interest rate pass-through for appropriate policy analysis and recommendation. Hence, our results should not be generalized.

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# Does Equity Derivatives Trading Affect the Systematic Risk of the Underlying Stocks in an Emerging Market: Evidence from Pakistan's Futures Market

**Safi Ullah Khan[*] and Zaheer Abbas[**]**

**Abstract**

*This paper examines the behavior of beta coefficients (systematic risk) for underlying stocks around the introduction of single-stock futures (SSFs) contracts in the Pakistani market, by employing models that account for nonsynchronous and thin trading and varying market conditions as "bull" and "bear" markets. Unlike the results of earlier studies on US markets, the empirical evidence tends to support a decline in systematic risk for the majority of underlying stocks in the post-futures listings period. Nevertheless, similar to SSFs stocks, we also find empirical evidence of a decrease in systematic risk for many of the control group stocks. This indicates that changes in beta estimates for SSFs-listed stocks might not be induced by the introduction of SSFs contract trading, but could be attributed to other market-wide or industry changes that have affected the overall market. Several plausible reasons, such as lack of program trading activities normally associated with index futures, market microstructure differences between developed markets and a developing market such as Pakistan, and the capturing of the "bear" and "bull" market effects on stock betas in our estimation procedure could explain these different results for Pakistan's market.*

**Keywords**: Systematic risk, beta, stock index futures, single-stock futures, stock price volatility, GARCH model, bear and bull markets, thin trading, Pakistan.

**JEL classification**: G10, G13.

## 1. Introduction

Single-stock futures (SSFs) are futures contracts written on individual shares (underlying assets), and were first introduced on the Australian market in 1996. Many markets have since made them available

[*] Institute of Management Sciences Kohat University of Science and Technology, Khyber Pakhtunkhwa, Pakistan.
[**] Faculty of Management Sciences, International Islamic University, Islamabad, Pakistan.

to investors and many more are contemplating introducing SSFs.[1] Though the effect of stock index futures trading on the price volatility of the underlying assets has been widely examined in finance literature, SSFs, being newer derivatives products, have not received much attention—in particular, their effect in emerging markets.[2] While SSFs are a useful addition to the range of instruments available to investors, providing a better match for investment and risk management purposes than the broad-based stock index futures, concerns about their impact on the underlying assets remain.

This paper examines one relatively neglected aspect of SSFs trading in the literature—the possible relationship between SSFs[3] contracts trading and the behavior of the systematic risks[4] of underlying stocks in Pakistan's equity market. The study contributes to the literature on the SSFs market in several ways. First, it extends the literature on SSFs to a market that has not yet been studied to examine SSFs trading in relation to the sensitivity of the underlying assets. Despite the fact that SSFs were introduced onto Pakistan's market much earlier than in many markets around the world, including the US market,[5] researchers have largely ignored the Pakistani market in this context. Two key exceptions are Khan (2006) and Khan and Hijazi (2009), who examine the relationship between SSFs trading and the price volatility of the underlying stocks in the Pakistani market, and report that SSFs trading has some soothing effect on the underlying stocks' level of volatility. Nonetheless, this market has not, by and large, captured researchers' attention. We attempt to fill this gap.

Moreover, though academic interest in SSFs trading and the underlying market is growing and a number of studies have examined the price and volatility dynamics of SSFs trading, to the best of our knowledge none have looked at SSFs trading and the beta relationships of the underlying stocks. Our paper aims to trigger further research on this topic.

Additionally, because of their unique characteristics, a study of SSFs contracts offers several advantages over the study of broad-based

[1] Presently, SSFs are available in Australia, the US, UK, South Africa, India, Malaysia, Hong Kong, and certain other markets.
[2] Studies by Vipul (2008) and Dawson (2007) are exceptions.
[3] SSFs are known as deliverable futures contracts (DFCs) in Pakistan, probably because of their physical settlement by delivery of the underlying shares. Cash-settled SSFs contracts are also available in some markets (for instance, in India).
[4] Systematic risk is a covariance of an asset's returns with that of market returns and is statistically measured by beta.
[5] It may be pertinent to mention that trading in SSFs in the US market was discontinued in the 1980s due to matters of regulatory jurisdiction and only allowed in 2003.

index futures contracts. First, the effect of index futures on the underlying asset may not be measured as accurately as the effect dissipates across many constituent stocks, whereas trading in SSFs-underlying stocks can be directly observed in the spot market, making it easier to accurately measure SSFs-related effects. Second, multiple introduction dates for SSFs mitigate the limitations of single-event studies of index futures, and help to evaluate their effect on underlying assets in different time periods. Hence, any impact of derivatives is likely to be more evident in the behavior of individual stocks than in an overall index returns.

Our empirical results are summarized as follows. We observe a significant decrease in beta estimates for many of the SSFs-listed stocks in the post-futures trading period. Nevertheless, a considerable number of control stocks also behave in a similar fashion. The results thus fail to reject the hypothesis that SSFs trading might not have an impact on the systematic risk of the SSFs-listed stocks, either in the short or long run. The next section reviews the theoretical and empirical literature, followed by a description of the data and methodology. The last section concludes the paper.

## 2. Literature Review

### *2.1. Theoretical Background*

No specific theories or models have been presented to explain why there should be any relationship between equity derivatives trading activities and the systematic risk or co-movements between individual securities and market returns. Nevertheless, two hypotheses are put forward as a possible explanation for the relationship between trading activities associated with stock index futures trading—such as program trading and portfolio insurance activities by large institutional investors—and the responsiveness of individual securities returns to market or index movements.

The first is the "price pressure hypothesis"[6] (Shleifer, 1986; Harris & Gurel, 1986), which finds widespread application in the literature on the inclusion of a stock in an index and the consequent short-term

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[6] This theory has been tested in a variety of markets and in a number of settings in an attempt to explain price reactions/effects, such as an increase in stock return volatility and trading volumes, to different events such as stock additions to or deletions from an index. See, for example, Shleifer (1986), Dhillon and Johnson (1991), and Elliot and Warr (2003) for the S&P 500 index; Brealey (2000) for the UK market; Chan and Howard (2002) for the Australian market; Trahan and Bolster (1997) and Keral and Walter (2006) for analyst buy recommendations; and Sias, Titman, and Starks (2001) for the price impact of institutional trading.

uncharacteristic increase in stock price volatility and trading volumes. After the inclusion (exclusion) of a stock in an index, there is a temporary rise (fall) in demand for the stock over a short period because of heavy trading caused by the rebalancing of the index tracking funds. Once these abnormal trading activities return to normal levels, the prices revert to and reflect the equilibrium levels, exhibiting a temporary increase in the trading volumes and variance of returns. Generalizing this to an index arbitrage and program trading activities, large institutional investors seeking to exploit arbitrage opportunities—in case a stock index futures price is higher (lower) than the value of the index itself—sell (buy) the futures and buy (sell) the underlying stocks, typically in a "basket" of stocks worth millions of dollars. Thus, one would find a portfolio of stocks reacting in a similar fashion, and this may lead to an increase in their degree of co-movement.

The second hypothesis that could explain the effect of program trading on stock returns is the "cascade theory", which posits that program selling aggravates declines in stock prices. Portfolio insurers typically carry out portfolio insurance adjustment strategies for large "baskets of stocks" by trading in index futures because of the lower transaction costs in the futures market compared to the cash market. They sell index futures rather than the underlying basket of stocks to hedge against market risk, leading to a decrease in the futures prices relative to the spot market value of the index. This decline in index futures relative to spot market prices induces index arbitragers to enter the fray and purchase futures, selling the underlying stocks. Thus, index arbitrage transmits to the cash market the portfolio insurers' selling pressure in the futures market, which causes further declines in cash market prices. This triggers further selling in futures by the portfolio insurers, which is again transmitted to the stock market by the arbitragers and so on, causing "downward cascading" in stock prices.

### *2.2. Empirical Evidence*

The empirical literature on the effect of derivatives trading on the systematic risk factors of underlying stocks is scarce, and often presents conflicting results. For instance, Skinner (1989) reports that, with the initiation of the options on stocks, the return volatility decreases while the beta is unaffected; Conrad (1989) gives similar results. In contrast, Martin and Senchack (1989) use monthly returns for stocks composed of the major market index (MMI) by employing an event study (before and after) methodology, and report an increase in the systematic risk for 20 MMI stocks after the introduction of MMI futures. They attribute this to the use of controversial techniques such as program trading[7] by investors in the US market.

Applying a more sound methodology than their earlier study, Martin and Senchack (1991) use daily returns data on MMI-constituent stocks and compare changes in the stock's percentage systematic risk with a control sample of 20 stocks that do not belong to an index with a traded futures/options contract. The results indicate an average increase in percentage systematic risk for the 20 MMI stocks. The nonindex stocks show little evidence of increased systematic risk. The study also reports an increase in average correlation between index stocks, which they do not find for nonindex stocks. These findings lead the authors to conclude that the increase in systematic risk for index stocks can be attributed to the program trading in the index stocks associated with the index futures contracts. Similar results are also reported by Vijh (1994) with significant increases in beta estimates for Standard and Poor's (S&P) 500 stocks relative to the nonindex stocks, which the author attributes in part to the price pressures or excess volatility caused by the S&P 500 trading strategies, which also include program trading activities.

Other studies, however, find no evidence of changes in the beta coefficients of the underlying index-constituent stocks. Galloway and Miller (1997) examine the effect of MidCap index futures trading on the changes in the systematic risk for stocks comprising the index and two control samples that consist of medium- and large-capitalization stocks. They use both OLS betas and those that are adjusted to account for nonsynchronous trading that might cause bias in the beta estimates, with various lead/lag structures. The study reports a significant decrease in beta estimates for samples of medium- and large-capitalization stocks while no such change is found for the component stocks in the MidCap index futures. These findings lead them to infer that trading in index futures has no effect on the systematic risk, beta coefficient, of the index stocks.

Kan and Tang (1999) analyze Hang Seng Index (HSI) (Hong Kong) futures-constituent stocks, applying a "varying risk market model" to daily stock return data in the context of the pre-versus-post-HSI futures period. They find no evidence of an increase in the systematic risk of HSI-

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[7] Program trading strategies are generated trading strategies that involve the simultaneous sale and/or purchase of a large basket of securities, and are used primarily for index arbitrage, market timing, and portfolio insurance. Though program trading can occur in different ways, the most widely known strategy is index arbitraging, which, as Martin and Senchack (1989) propose, "involves purchasing (selling) the cash stock portfolio and simultaneously selling (purchasing) the index futures contract when the futures price exceeds (is less than) the spot price of the index, net of the cost carry."

constituent stocks in the post-futures trading period either in the short or long run. Since then, few studies have focused on this issue, though much has been written on the volatility effects of futures trading.

Numerous empirical studies have found that beta estimates can be biased because of nonsynchronous trading and market frictions such as thin trading, trading delays, and price adjustment delays. This can cause the beta estimate to be biased toward zero—the bias is known as the "Epps Effect" (Epps, 1979) and is reported in Dimson (1979) and Hayashi and Yoshida (2005). The phenomenon of nonsynchronous trading occurs primarily in markets characterized by thin trading as closing prices are recorded at the close of the session. These prices can reflect transactions that had occurred well before the close of the session for many stocks. Iqbal and Brooks (2007) acknowledge and document the infrequent trading characterizing the Karachi Stock Exchange, and accordingly adopt Dimson's (1979) technique to correct the bias in their beta estimations.

## 3. The SSFs Market in Pakistan

SSFs were introduced on the Karachi Stock Exchange (KSE)—the largest of Pakistan's three exchanges—on 1 July 2001. Initially, nine stocks were selected for SSFs contracts listed on the exchange. The number of SSFs contracts were increased in phases to a total of 46 stocks by February 2008. Overall, these 46 contracts provide market coverage to each of the major sectors of Pakistan's economy: commercial banks (17 SSFs), textiles (one SSF), cement (five SSFs), power generation and distribution (three SSFs), oil and gas marketing (three SSFs), oil and gas exploration (three SSFs), synthetics and rayon (two SSFs), transport (one SSF), technology and communication (two SSFs), refineries (four SSFs), insurance (one SSF), and fertilizers (three SSFs).

Trading in SSFs takes place through the computerized Karachi Automated Trading System and is displayed on KSE's market information system. SSFs contracts are available on a one-calendar-month expiry cycle,[8] with the last Friday of the month as the last trading day in a contract, and are settled on the following Wednesday through a KSE clearinghouse as there is no separate, independent futures exchange for SSFs trading in Pakistan. SSFs contracts are settled through the physical delivery of shares on the expiration

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[8] Recently, the KSE introduced 90-day, cash-settled SSFs in a few scrips. These were initially introduced in only three stocks, but the KSE plans to gradually increase them to other stocks. The KSE has only recently introduced stock index futures with the KSE-30 index as the underlying asset. The introduction of all these different types of equity derivatives does not coincide with our sample time period in order to avoid confounding our empirical results.

of the contract since there is no option for cash settlement, and final holder of the futures contract has to take delivery of the underlying stocks.[9]

Contracts for different months can trade on the exchange at the same time. There is an overlapping period for contracts: the period for the new contract can start at least two trading days before the close of the old one. A circuit breaker is put in place if there is a price fluctuation of 7.5 percent or PKR 1.5, whichever is higher, compared to the previous day's closing price. The Annex summarizes the salient contract specifications of SSFs contracts traded on the KSE.

## 4. Varying-Risk Market Model for Evaluation of Risk Estimates

In order to examine changes in beta for SSFs-listed stocks—as modeled by the capital asset pricing model (CAPM)—after the introduction of SSFs contracts for those stocks, we estimate pre-event and post-event betas for each stock. Earlier empirical applications of the CAPM and studies such as Rowe and Kim (2010), Yip and Lai (2009), and Frimpong (2010) have used the market model approach, which assumes a constant beta. Numerous studies show that systematic risk varies over time, with different variables describing the financial structure (see, for example, Ulosoy, 2008; Rowe & Kim, 2010; Patton & Verado, 2009) or the business cycle (see Shanken, 1990; Ferson & Schadt, 1996).

Some studies have documented changes in beta estimates for individual stocks under varying market conditions, i.e., "bull" and "bear" markets. Fabozzi and Francis (1977, 1979), for instance, report varying beta and alpha estimates for stocks in bull and bear markets. Francis and Fabozzi (1979) and Jagannathan and Wang (1996) also report similar results. Howton and Peterson (1998) document the relationship between beta and stock returns that changes in bull and bear markets even after controlling for other determinants of stock returns such as size, book-to-market ratio, and earnings–price ratio. Their findings highlight the importance of using a varying-risk model to estimate stock betas.

Damodaran (1990) employs daily returns data to compare beta changes for S&P 500-constituent stocks and nonindex firms, and finds, on average, higher betas for S&P 500 index stocks in the post-futures period compared to nonindex stocks, which reveal, on average, no change in betas. Even after accounting for firm-specific fundamental (accounting) variables (such as dividend yields, D/E ratio, book value of assets, and

[9] Physical settlement is implemented in both One Chicago and NQLX exchanges in the US market, in contrast to cash settlement in LIFFE Universal Stock Futures contracts (UK).

cash-to-total assets), the author concludes that this increase in beta could be related to trading activity variables, which show much more trading and noise subsequent to the index futures trading.

In light of the discussion above and the methodologies used by previous studies to account for varying market conditions, we employ a varying-risk market model to control for the possible differential return premiums between bull and bear markets. Following Kan and Tang (1999), we adopt the following varying-risk market model to examine SSFs trading and systematic risks effects:

$$R_{i,t} = \varphi_1 + \varphi_2 D_1 + \varphi_3 D_2 + \varphi_4 D_1 D_2 + \beta_0 R_{m,t} + \beta_1 D_1 R_{m,t} + \beta_2 D_2 R_{m,t} + \beta_3 D_1 D_2 R_{m,t} + \varepsilon_{i,t} \quad (1)$$

EMBED Equation.3 $R_{i,t}$ are the weekly returns on a stock $i$ for week $t$ $t - i \times 100-$. The risk-free rate is the annualized 90-day government t-bill rate and is adjusted on a weekly basis. $R_{m,t}$ is the return on the KSE-100 index, taken as a proxy for overall market returns; the excess returns on the market portfolio are calculated in a similar fashion. $D_1$ and $D_2$ are dummy variables, where $D_1$ is equal to 1 in the post-SSFs period and 0 in the pre-SSFs period, while $D_2$ is equal to 1 in bear months and 0 in bull months in either the post-futures or pre-futures period.

The model also allows slope dummies to vary in the post-SSFs period. The product of $D_1$ and $D_2$ is, therefore, incorporated in the equation to account for the possibility that the "bull and bear market" effects on the stock beta can be influenced by the initiation of SSFs trading.

In equation (1) when $D_1 = 1$, the beta coefficient is $\beta_0 + \beta_1 + \beta_2 D_2 + \beta_3 D_2$; when $D_1 = 0$, it is $\beta_0 + \beta_2 D_2$. Therefore, the change in the beta coefficient for a particular stock in the pre-SSFs and post-SSFs period is $\beta_1 + \beta_3 D_2$. The statistical significance of $\beta_1 + \beta_3 D_2$ indicates whether the beta of a stock has changed after SSFs trading has been introduced. If the $\beta_3$ coefficient turns out to be statistically insignificant, $\beta_1$ may be used to measure changes in the stock's beta in the post-futures period.

There are several definitions of bear and bull markets in the literature. In this study, each month of the sampling interval is categorized as a bull month (with positive rates of return) or a bear month (with negative rates of return), using the definition given by Kan and Tang (1999). This definition is similar to Fabozzi and Francis's (1979) definition of "up and down markets".

## 5. Data Description and Empirical Results: Varying-Risk Market Model

The data we have used consists of the weekly closing prices of SSFs-listed stocks and a sample of matching non-SSFs stocks for a ten-year period from 1 July 1999 to 31 December 2009. For each SSFs contract, we consider two years' data for the pre-SSFs period and two years' data for the post-SSFs period. The weekly price data is taken as the closing price on Wednesday of each week to avoid any day-of-the-week or weekend effects. We include all 46 SSFs stocks listed on the KSE in our sample. The sample interval for each stock is divided into two sub-periods, i.e., the pre-SSFs period and post-SSFs period, and each sub-period consists of two years' data for each stock during the sample period.

In an attempt to determine whether the changes, if any, in the betas of the SSFs-listed stocks can be attributed to the introduction of futures contracts or whether they are the result of general market or industry-specific changes, we also include a control sample of non-SSFs stocks. Non-SSFs stocks are selected from all the major sectors of the economy to ensure that the market is fairly represented. A total of 88 stocks are included in the control group, which, together, comprise about 80 percent of the market's capitalization and represent 18 sectors of the economy. We use the KSE-100 index, a market capitalization-weighted index, to proxy for market returns, and the closing values of the index on the Wednesday of each week to calculate weekly index returns. The index values are adjusted for dividends. The KSE is benchmarked by the KSE-100 index, which represents more than 80 percent of the market's capitalization.

Changes in betas may reflect microstructure price effects or merely changes in true betas. We investigate this issue by examining measured betas over short- and long-window intervals around SSFs listings. We expect true betas to depend on the riskiness inherent in firms' cash flows—it is less likely that their cash flows will become riskier all of a sudden and in such a short period of time. On the other hand, market microstructure effects can be reflected in prices and, hence, in betas, soon after an event such as the introduction of SSFs contracts for stocks.

Equation (1) is, therefore, applied separately to each of the SSFs-listed and non-SSFs stocks for pre-SSFs and post-SSFs periods over three different sampling intervals (six months, 12 months, and two years) to determine the impact of SSFs trading in the short term, medium term, and longer term, respectively. The empirical results (not reported in this study) show that the $\beta_3$ coefficient is not statistically significant for the majority of

SSFs-listed and non-SSFs stocks across all three sampling intervals. The $\beta_1$ coefficient can, therefore, be used to estimate if the systematic risk (beta coefficient) of SSFs stocks has changed in the post-SSFs trading period.

Table 1 gives the number and percentage of stocks for changes (significant increase, decrease, or no change) in the beta coefficient for SSFs and a sample of non-SSFs stocks for three different sampling intervals (six-month, one-year, and two-year periods). The table indicates no systematic pattern in the change (increase or decrease) in beta coefficients either for the SSFs or the sample of non-SSFs stocks in the post-futures period. For instance, in the case of the six-month interval, the beta coefficients for nine (19.6 percent) SSFs stocks and another 11 (23.9 percent) SSFs-listed stocks exhibit a significant increase and decrease, respectively, after futures trading begins for these stocks. More than 56 percent of SSFs stocks undergo no significant change in the systematic risk coefficient for the same period.

**Table 1: Percentage of stocks with beta changes for SSFs-listed and non-SSFs stocks (post- and pre-futures periods for different sampling periods)**

| **SSFs-listed stocks** | **6 months' time** | **1 year's time** | **2 years' time** |
|---|---|---|---|
| Increases in beta | 9 (19.57%) | 9 (19.57%) | 5 (10.86%) |
| Decreases in beta | 11 (23.89%) | 18 (39.30%) | 25 (54.38%) |
| No changes in beta | 26 (69.23%) | 19 (41.13%) | 16 (34.78%) |
| Total | 46 (100%) | 46 (100%) | 46 (100%) |
| **Non-SSFs stocks** | **6 months' time** | **1 year's time** | **2 years' time** |
| Increases | 5 (5.6%) | 18 (20.45%) | 13 (14.778%) |
| z-statistic | [0.681] | [-0.0652] | [-0.7993] |
| Decreases | 9 (10.22%) | 26 (29.54%) | 37 (42.04%) |
| z-statistic | [1.1599] | [0.597] | [-0.0774] |
| No changes | 74 (84.10%) | 44 (50%) | 38 (43.18%) |
| **Test statistic** | | | |
| z-statistic | [-1.243] | [-0.5741] | [-0.5704] |
| Total | 46 (100%) | 46 (100%) | 46 (100%) |

**Note:** The words 'increases' and 'decreases' represent the number and percentage of stocks with a significant increase or decrease in the post-futures period, while 'no change' represents the number of stocks with no significant change in beta estimates. The detailed results for each stock are not reported here and can be provided on request.
***Source***: Authors' calculations.

For the sample of non-SSFs stocks for same period (six-month interval), five (5.6 percent) stocks and another nine (10.2 percent) non-SSFs stocks exhibit a significant increase and decrease, respectively. However, the majority of non-SSFs stocks undergo no significant change in their beta coefficients. For longer sample intervals (one- and two-year periods), there is a slight increase in the number of stocks (both SSFs-listed and control group stocks) whose beta estimate falls in the post-futures period.

To test whether the SSFs-listed stocks' beta changes are different from those of the control group stocks across each of the three sampling intervals, we calculate the z-statistics for each (reported in the last panel of the table). The test statistic indicates no significant difference in the proportion of stocks with significant changes (increase or decrease) between SSFs-listed and non-SSFs stocks for each of the three sampling intervals. These results indicate that SSFs trading might not have an impact on the betas of the SSFs-listed stocks either in the short or long run.

## 6. Discussion and Conclusion

We have examined changes in the beta coefficients (systematic risk) of the underlying stocks post-SSFs listings in Pakistan's market by employing a model that accounts for nonsynchronous trading and varying market conditions such as bull and bear markets. Unlike the results of some earlier studies on the US market, our empirical evidence tends to support a decline in systematic risk for the majority of the underlying stocks subsequent to futures listings.

Nevertheless, as pointed out by McKenzie, Brailsford, and Faff (2001), this reduction in beta could also be attributed to market-wide movements. We therefore consider the results for a control group, and in line with our results for SSFs stocks, find empirical evidence of a decrease in systematic risk for many of the non-SSFs listed stocks. This shows that changes in beta estimates for SSFs-listed stocks might not necessarily be induced by the introduction of SSFs trading for those stocks but could be attributed to other market-wide or industry-related changes that have affected the overall market. These results for Pakistan's SSFs market are consistent with the findings of Galloway and Miller (1997) who attribute apparent changes in the risk of index stocks to market-wide changes that are not associated with the initiation of index futures.

Several plausible reasons could explain these different results for Pakistan's market. One is the market's lack of program trading activities—

the main reason emphasized by Martin and Senchack (1989) and Damodaran (1990) as a cause of an increase in systematic risk of the index constituent stocks. Another possible reason is the use of a methodology that allows us to capture bull and bear market effects on stock betas, which previous studies have not accounted for; the changes in beta in these studies could be attributed to bear and bull market conditions rather than to index futures trading. Additionally, market microstructure differences between more developed markets and emerging markets such as Pakistan are a possible reason for the differences in our findings. Nevertheless, our study leaves scope for further research in this context, but does show that SSFs trading does not necessarily have any impact on the underlying stock's co-movement with the market.

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## *Annex*

**Specifications of SSF contracts traded on the Karachi Stock Exchange**

| | |
|---|---|
| Period of contract | 1 calendar month |
| Expiration date/last trading day | Last Friday of the calendar month; if the last Friday is not a trading day, the immediate preceding trading day. |
| Final settlement | Physical delivery of underlying shares on the basis of T+2, falling immediately after the close of contract. |
| Initial margin | 50% cash of the total value of the contract[10] |
| Settlement day | Wednesday following the last Friday of the calendar month |
| Settlement method | Physical delivery of the underlying shares |
| Overlapping period | None. Contract for different months can trade at the same time. |
| Contract size | Larger than or equal to that of a marketable lot |
| | In the underlying share in ready market |
| Opening of contract | At least two days before the close of the old contract period. |
| Regular trading hours | Monday–Thursday: 0945–1415 |
| | Friday: 0930–1200 and 1430–1600 |
| Corporate events | SSFs contracts adjusted to reflect changes to underlying stocks |
| Quotations/tick size | PKR 0.05 per share |
| Contract size | 500 shares |
| Contract multiplier | 500 shares, subject to changes when adjustments are made with respect to corporate events. |
| | Contract value = futures price x contract multiplier |
| Position limits | Individual broker or client-wise position limit is 1% of the free float of a scrip |

***Source:*** Adapted from the Karachi Stock Exchange's "Regulations governing deliverable futures contracts 2004".

[10] In the new rules, amended in 2010, the initial margin has been increased to 100 percent cash or bank guarantee.

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# The Co-determinants of Capital Structure and Stock Returns: Evidence from the Karachi Stock Exchange

**Hamid Ahmad[*], Bashir A. Fida[**] and Muhammad Zakaria[***]**

**Abstract**

*This study uses a structural model to analyze the co-determinants of capital structure and stock returns. Applying a generalized method of moments (GMM) model to a panel dataset for 100 nonfinancial firms for the period 2006–10, our results indicate that both leverage and stock returns affect each other but that the former has a dominant effect on the latter. The results illustrate that profitability, growth, and liquidity are significant determinants of leverage and stock returns. Profitability negatively affects leverage and positively affects stock returns. Growth has a positive effect, while liquidity has a negative effect on leverage and stock returns. Firm size does not have any significant effect on either capital structure or stock returns.*

**Keywords:** Capital structure, stock returns, GMM, Pakistan.

**JEL classification:** C33, C36, G30.

## 1. Introduction

Capital structure is an amalgam of a firm's liabilities and equity. Capital structure and composition is a crucial aspect of business, and plays a vital role in firms' survival, performance, and growth (Voulgaris, Asteriou, & Agiomirgianakis, 2004). Firms choose different levels of financial leverage in their attempt to achieve an optimal capital structure, and capital structure policy involves a tradeoff between risk and return. An increase in debt intensifies the risk of a firm's earnings, which leads to a higher rate of return to investors. High risk tends to lower the stock's price, while a high rate of return increases it, so the firm's capital structure policy determines its returns.

Capital structure, stock returns, and their determinants have garnered considerable attention among researchers in financial

[*] Instructor, Virtual University of Pakistan.
[**] Assistant Professor, COMSATS Institute of Information Technology, Islamabad, Pakistan.
[***] Assistant Professor, COMSATS Institute of Information Technology, Islamabad, Pakistan.

management. Although many studies have examined the determinants of either capital structure or stock returns, few have investigated both. Some show that stock returns determines capital structure (Baker & Wurgler, 2002; Welch, 2004), while others argue the opposite: that capital structure determines stock returns (Bhandari, 1988). Some studies show that capital structure and stock returns affect each other simultaneously (Yang, Lee, Gu, & Lee, 2010). However, no such study has been conducted in the context of Pakistan that shows the simultaneous interaction between capital structure and stock returns. We start with the premise that capital structure and stock returns are interrelated, and are primary determinants of one another since they play an important role in optimal business decision-making.

There is a dearth of literature on this subject in the context of Pakistan. Although studies on Pakistan have identified different determinants of capital structure—including tangibility, firm size, growth, earning volatility, profitability, nondebt tax shield, and income variation (Hijazi & Tariq, 2006; Rafiq, Iqbal, & Atiq, 2008; Shah & Hijazi, 2004; Shah & Khan, 2007; Sheikh & Wang, 2011)—none incorporate stock returns as a determinant. Furthermore, no empirical work has been conducted on Pakistan that explains the effect of capital structure on stock returns. Previous studies identify only dividends and earnings per share as firm-specific variables that can affect stock returns (Azam, 2011). No study shows the simultaneous interplay between capital structure and stock returns. This study tries to fill that gap.

The rest of the paper is organized as follows. Section 2 provides a theoretical framework. Section 3 presents an overview of the data used, and estimates and interprets the model. Section 4 concludes the paper.

## 2. The Model

This section derives a theoretical model that will be empirically estimated in the following section. In line with the previous research on this topic (see, for instance, Chen & Chen, 2011; Yang et al., 2010), our proposed econometric model is as follows:

$$Lev_t = \beta_0 + \beta_1 SR_t + \beta_2 SZ_t + \beta_3 PF_t + \beta_4 GW_t + \beta_5 LQ_t + \mu_t \tag{1}$$

$$SR_t = \alpha_0 + \alpha_1 Lev_t + \alpha_2 SZ_t + \alpha_3 PF_t + \alpha_4 GW_t + \alpha_5 LQ_t + \nu_t \tag{2}$$

where the following variables are defined as given:

$Lev_t$ = leverage

$SR_t$ = stock returns

$SZ_t$ = size of firm

$PF_t$ = profitability

$GW_t$ = growth of firm

$LQ_t$ = liquidity ratio

$\mu_t$, $\nu_t$ = white noise error terms

Each of the included variables and the relevant theory that justifies their inclusion in the model are explained below.

- *Stock returns:* A higher stock return increases the market value of assets and, hence, the debt ratio decreases (Yang et al., 2010). This implies that stock returns negatively affects leverage $(\beta_1 < 0)$.
- *Leverage:* Theoretically, if a firm is highly leveraged, then the investor will demand a higher return on its stock due to the high risk of bankruptcy (Bhandari, 1988; Yang et al., 2010). Therefore, one would expect leverage to have a positive effect on stock returns $(\alpha_1 > 0)$.
- *Size of firm:* According to the tradeoff theory, larger firms, which are more diversified, have lower bankruptcy costs, and easier access to capital markets, obtain more debt. The pecking order theory, however, suggests that larger firms rely on internal sources of finance and, hence, do not choose debt or equity as their first option for financing. Empirically, studies have found that larger firms borrow more in order to take maximum advantage of tax shields. Thus, firm size is expected to have a positive effect on leverage $(\beta_2 > 0)$. Since smaller firms may suffer from earnings depression and information asymmetry, it involves more risk than larger firms, and investors demand more return on their stock (Gallizo & Salvador, 2006). Hence, firm size is expected to have a negative effect on stock returns $(\alpha_2 < 0)$.
- *Profitability:* The pecking order theory of capital structure implies that profitable firms will not opt for debt or equity financing because they have sufficient funds to finance their assets. However, the tradeoff theory proposes a positive relationship between profitability and

leverage. Intuitively, this suggests that higher-profit firms can, on the strength of their reputation, easily acquire debt and take maximum advantage of tax shields. Hovakimian, Opler, and Titman (2001) argue that there is no association between profitability and leverage because unprofitable firms also issue equity to offset the effect of excessive leverage. Empirically, a negative relationship emerges between firm profitability and leverage (Chen & Chen, 2011; Yang et al., 2010). Thus, we expect profitability to have a negative effect on leverage $(\beta_3 < 0)$. Since higher-profit firms provide more return on their stocks, profitability should have a positive effect on stock returns $(\alpha_3 > 0)$.

- *Growth:* According to the pecking order theory, if a firm's internal sources are not enough to fund new projects, it will opt for debt financing. This shows that high-growth firms are highly leveraged because they can acquire more debt due to their need for greater financing. The trade-off theory hypothesizes that growth opportunities cannot be collateralized to acquire debt and that growing firms have enough resources to finance new activities. So, there is a negative relationship between growth and leverage. Empirical studies have also found that growth has positive and negative effects on leverage. Thus, the sign of $\beta_4$ cannot be determined a priori. Chen and Chen (2011) explain that a firm's growth causes variation in its value, and greater variation is associated with greater risk. This implies that growth positively affects stock returns $(\alpha_4 > 0)$.

- *Liquidity:* The pecking order theory explains that retained earnings increase liquid assets; excess liquid assets are negatively associated with firm leverage. The trade-off theory suggests that firms with a high ratio of liquid assets should borrow more because they have the ability to meet their contractual obligations on time. This theory predicts a positive relationship between liquidity and leverage. Based on the empirical studies carried out, firms with high levels of liquid assets are likely to acquire less debt and rely on internally generated funds. Thus, liquidity should negatively affect leverage $(\beta_5 < 0)$. While analyzing the effect of liquidity on stock returns, many empirical studies have found a negative relationship between liquidity and stock returns. Most theoretical and empirical studies have demonstrated that liquidity has a negative effect on stock returns since liquid stock involves less risk, so the return on liquid stock is low (Chen & Chen, 2011; Yang et al., 2010). Thus, there is a negative relationship between liquidity and stock returns $(\alpha_5 < 0)$.

## 3. Data, Estimation, and Interpretation of Results

### *3.1. Data Overview*

Following the standard practice, leverage is calculated as the ratio of total liabilities to total assets. Total liabilities (assets) include short-term and long-term debt (assets). Stock returns are measured as the ratio of the market value to book value of equity. The market value of equity is calculated as the product of price per share and common shares outstanding, while the book value of equity is calculated as total assets minus total liabilities and preferred stocks. The log of the firm's total sales is used as a proxy for firm size. Profitability is calculated as the ratio of net profit before taxes to total assets of the firm. Firm growth is measured by the percentage change in total assets. Liquidity is measured as the ratio of current assets to current liabilities.

Data was collected for 100 nonfinancial companies listed on the Karachi Stock Exchange (KSE) for the period 2006–10, and taken from the State Bank of Pakistan, the KSE, the *Business Recorder*, and companies' annual reports.

Table 1 provides summary statistics for the variables used in this study, which helps interpret the coefficient estimates by providing the scale of the relevant variables.

**Table 1: Summary statistics for variables used**

| Variable | Mean | Median | Std. dev. | Minimum | Maximum | Count |
|---|---|---|---|---|---|---|
| Leverage | 0.65 | 0.66 | 0.25 | 0.02 | 1.67 | 500 |
| Stock returns | 1.15 | 0.65 | 5.65 | -65.30 | 56.25 | 500 |
| Size | 14.69 | 14.55 | 1.74 | 7.35 | 18.87 | 500 |
| Profitability | 0.05 | 0.02 | 0.14 | -0.38 | 0.74 | 500 |
| Growth | 0.11 | 0.07 | 0.22 | -0.61 | 1.20 | 500 |
| Liquidity | 1.31 | 0.99 | 1.20 | 0.00 | 9.66 | 500 |

***Source***: Authors' calculations.

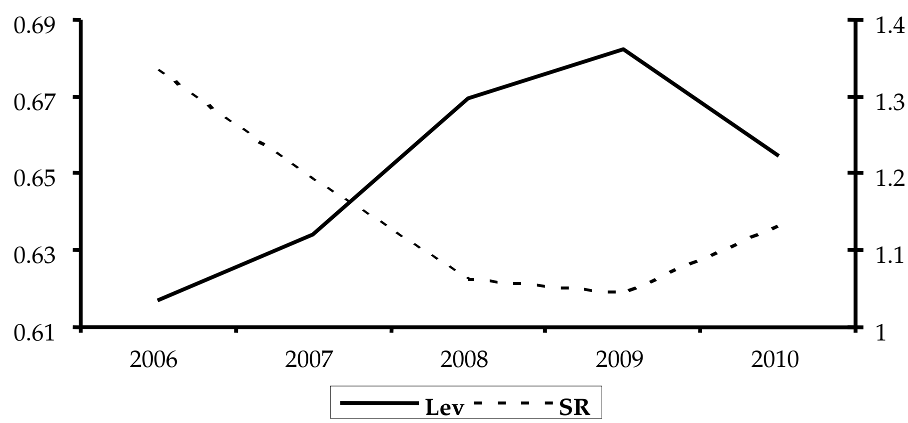
Table 2 presents the correlation matrix for the variables. Column (1) of Table 2 correlates leverage with all the independent variables. The value of the correlation coefficient of stock returns is -0.234, which indicates that leverage and stock returns are inversely correlated with each other. This result is also supported by Figure 1, which illustrates the trend analysis between leverage and stock returns.[1] It is evident from the figure that both variables are inversely related with one another. This statistical analysis remains, however, simplistic, and calls for a more rigorous framework, which is done in the next section.

**Table 2: Correlation matrix of variables**

| Variable | Leverage | Stock returns | Size | Profitability | Growth | Liquidity |
|---|---|---|---|---|---|---|
| Leverage | 1.000 | | | | | |
| Stock returns | -0.234 | 1.000 | | | | |
| Size | -0.106 | 0.076 | 1.000 | | | |
| Profitability | -0.540 | 0.161 | 0.340 | 1.000 | | |
| Growth | -0.121 | 0.066 | 0.234 | 0.221 | 1.000 | |
| Liquidity | -0.643 | 0.081 | -0.025 | 0.519 | 0.085 | 1.000 |

*Source*: Authors' calculations.

**Figure 1: Trend analysis between leverage (Lev) and stock returns (SR)**




*Source*: Authors' calculations.

### 3.2. *Estimation and Interpretation of Results*

We cannot use least squares to estimate our structural model because the potential endogeneity of the variables might render the least-square estimators biased and inconsistent. Therefore, we use the generalized method of moments (GMM) (see Arellano & Bond, 1991; Arellano, 1993; Arellano & Bover, 1995) to estimate our panel model. GMM

[1] Period average values are taken for the companies.

estimators control for the potential endogeneity of the lagged dependent variable, and for that of other explanatory variables in the model (Judson & Owen, 1999). The lagged values of the variables are used as instruments.

The results of the structural model are reported in Table 3. Column (1) gives the results of the leverage equation. The t-statistic for the stock returns coefficient (-2.9929) indicates that there is a statistically significant negative relationship between stock returns and leverage. The coefficient for stock returns is -0.0011, which means that a one-standard deviation increase in stock returns (5.65) leads to a -0.0062 decrease in leverage. Although, statistically, this result is significant, economically it is very weak. The result is consistent with the market timing theory of capital structure, which states that, when the return on a stock is high, a firm's managers will focus on equity financing rather than debt financing, thereby decreasing the firm's leverage. This negative relationship between stock returns and leverage shows that Pakistani firms do consider stock returns an important factor when determining an optimal capital structure.

The results for the other variables are also in line with theoretical predictions. Firm size affects leverage negatively. This result is consistent with the pecking order theory, which suggests that larger firms have internal sources of financing, and therefore do not opt for debt or equity as their first option. However, this result is statistically insignificant, implying that size is not an appropriate explanatory variable of debt ratio. The result reflects the findings of empirical studies on Pakistani firms that have also demonstrated that firm size does not have a significant relationship with leverage (Hijazi & Tariq, 2006; Shah & Khan, 2007).

Profitability has a significant negative effect on leverage, which implies that, in Pakistan, profitable firms do not prefer debt or equity financing because they have sufficient funds with which to finance their assets. Firm growth significantly and positively affects leverage. This result is in accordance with the pecking order theory that firms acquire more debts to fund new projects. The coefficient of growth indicates that a one-unit increase in growth will tend to increase leverage by 0.0319 units. Liquidity has a significant negative effect on leverage. This result also complies with the pecking order theory that firms with high levels of liquid assets will acquire less debt and rely more on internally generated funds.

Column (2) gives the results for the stock returns equation. The t-statistic for the leverage coefficient (-3.0032) indicates that there is a statistically significant negative relationship between leverage and stock returns. The coefficient of leverage is -4.6199, which means that a one-standard deviation increase in leverage (0.25) leads to a -1.1550 decrease in stock returns. Unlike the weak effect of stock returns on leverage, however, the effect of leverage on stock returns is statistically strong.

Our results are in line with those of Chen and Chen (2011), who argue that firms with greater leverage face a higher risk of bankruptcy—investors accordingly feel more anxious when investing in the stocks of highly leveraged firms, and such investor behavior causes the value of the stock to fall. Furthermore, lenders impose different kinds of restrictions on firms, which can adversely affect the latter's performance. For example, lenders may restrict companies from using borrowed money in risky projects. Such restrictions can affect firms' performance negatively, making them unable to generate more return on their stock. The coefficient of firm size is insignificant, which means that the variable has no effect on stock returns—a result that goes against the theoretical expectation that firm size affects stock returns. The results also show that profitability has a significant positive effect on stock returns, i.e., high-profitability firms provide a high return on their stock in Pakistan.

As theoretically expected, firm growth significantly and positively affects stock returns. This result is in line with the notion that investors consider the stocks of growing firms more valuable because they expect a high future return and accord more worth to the stock of growing firms. This investor behavior causes an increase in the market value of the stock compared to its book value, which is an indication of high stock returns. It implies that growing Pakistani firms provide more return on their stocks. Finally, liquidity has a significant negative effect on stock returns. This result shows that firms with greater liquid stocks provide low (required) returns on their stock because stocks with high liquidity carry no risk and investors will purchase such stocks even at a low (required) return. As far as the relationship between leverage and stock returns is concerned, our results indicate that both have an opposite effect on each other: An increase in leverage decreases stock returns and an increase in stock returns decreases leverage. However, this negative influence is more dominant in the case of the effect of leverage on stock returns.

Columns (3) and (4) give seemingly unrelated (SUR) regression estimates. The SUR estimator, while inconsistent (no instruments are used), is characterized by greater efficiency and may prove some indication of the model's robustness. The SUR estimates provide almost the same results as the GMM estimates, but the significance levels of the variables have decreased greatly, and some variables have also become insignificant.

We have applied an autoregressive (AR) process to remove the problem of autocorrelation from the models. High values of $R^2$ and adjusted $R^2$ in the leverage equation indicate that the model fits the data fairly well. However, low values of $R^2$ in the stock returns model indicate that other variables—that have not been included in the model—also affect stock returns. The Durbin Watson (DW) values are close to the desired value of 2, which indicates the absence of an autocorrelation problem in the model. The high p-value of the J-statistic indicates that the instruments are valid.

**Table 3: Estimated results of model**

| | **GMM estimates** | | **SUR estimates** | |
|---|---|---|---|---|
| | **Leverage** | **Stock returns** | **Leverage** | **Stock returns** |
| **Variable** | **(1)** | **(2)** | **(3)** | **(4)** |
| Intercept | 0.9286 | 7.3139 | 0.7777 | 11.5345 |
| | (5.2460)* | (2.3452)* | (5.2720)* | (2.1528)* |
| Stock returns | -0.0011 | | -0.0027 | |
| | (-2.9929)* | | (-3.4116)* | |
| Leverage | | -4.6199 | | -10.4364 |
| | | (-3.0032)* | | (-4.3464)* |
| Size | -0.0078 | -0.1630 | 0.0032 | -0.1806 |
| | (-0.7315) | (-0.9244) | (0.3687) | (-0.5615) |
| Profitability | -0.2727 | 5.2585 | -0.3089 | 3.4174 |
| | (-4.0313)* | (2.6621)* | (-6.3007)* | (1.0634) |
| Growth | 0.0319 | 1.1462 | 0.0377 | 2.4075 |
| | (1.6542)** | (2.0412)* | (2.2110)* | (2.0013)* |
| Liquidity | -0.0653 | -0.5186 | -0.0458 | -0.7997 |
| | (-6.9983)* | (-2.2713)* | (-6.4625)* | (-1.8082)** |
| AR (1) | 0.9215 | 0.5695 | 0.9236 | 0.5853 |
| | (45.2242)* | (5.0648)* | (40.5632)* | (11.6663)* |
| $R^2$ | 0.8759 | 0.2951 | 0.8775 | 0.2922 |
| Adjusted $R^2$ | 0.8740 | 0.2843 | 0.8756 | 0.2814 |
| DW | 2.1675 | 1.9067 | 2.1366 | 1.9514 |
| J-statistic | 0.0501 | | | |
| p-value (J-statistic) | 0.9999 | | | |

**Note:** Values in parentheses are underlying student-*t* values. The *t* statistics significant at 5% and 10% levels of significance are indicated by * and **, respectively.
***Source***: Authors' calculations.

## 4. Conclusion

This study has used a structural model to find the co-determinants of capital structure and stock returns, employing a panel dataset for 100 nonfinancial firms listed on the KSE for the period 2006–10. The GMM was used to estimate the model and overcome the potential endogeneity problem. The results show that stock returns and leverage affect one another but that the effect of leverage on stock returns is greater than the effect of stock returns on leverage. The results also indicate that profitability, growth, and liquidity are significant determinants of both leverage and stock returns. Profitability affects leverage negatively and affects stock returns positively. Growth has a positive effect and liquidity has a negative effect on leverage and stock returns. Firm size, however, does not have any significant effect on either capital structure or stock returns.

Our results show that the pecking order theory of capital structure best explains the financing behavior of Pakistani firms. This suggests that they do not have a specific debt ratio; rather, they follow a hierarchy in their methods of financing. The results also indicate that Pakistani nonfinancial sector firms prefer to use internal sources of financing over external sources. As far as stock returns is concerned, the results support the market timing theory in best explaining the financing decisions of Pakistani firms: Firms will issue equity when the return on a stock increases.

Future research could extend the scope of the study to include a large number of nonfinancial companies and financial companies over a longer period. Adding other determinants such as asset structure, tax shield, business risk, and earning volatility to the variables used in this study may provide additional insights.

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# The Export Supply Response of Mangoes: A Cointegration and Causality Analysis

**Abdul Ghafoor[*], Khalid Mushtaq[**] and Abedullah[***]**

**Abstract**

*This paper analyzes the impact of major factors on the export of mangoes from Pakistan. We use a cointegration approach and error correction mechanism applied to data for the period 1970–2005. Mango exports are regressed against the index of relative prices of mango exports (2000 = 100), the quantity of domestic mango production, real agricultural gross domestic product (GDP), the length of all-weather roads, and international standardization, i.e., the impact of the World Trade Organization agreement. The results of the augmented Dickey-Fuller test reveal that all the data series are I(1). Applying Johansen's test shows that the highest elasticity coefficients are found for mango production in the short and long run, followed by real agricultural GDP. The Granger causality test points to the bi-directional causality of mango exports with the relative price index and all-weather roads, and unidirectional causality with real agricultural GDP and mango production. The study recommends promoting proper orchard management, developing the appropriate infrastructure, and stabilizing export prices to increase mango exports from Pakistan.*

**Keywords**: Mango, unit root, cointegration, Granger causality, Pakistan.

**JEL classification:** Q11.

## 1. Introduction

Agriculture is pivotal to Pakistan's economy. Despite the structural shift toward industrialization, agriculture still contributes 21.8 percent to the country's gross domestic product (GDP). It provides a livelihood for about 45 percent of the total employed labor force and contributes significantly to export earnings (Pakistan, Ministry of Finance, 2009). The total value of agriculture at constant factor cost (1999/2000) was estimated

[*] Assistant Professor, Institute of Business Management Sciences, Faculty of Agricultural Economics and Rural Sociology, University of Agriculture, Faisalabad.
[**] Agricultural Economist, Rural Finance Resource Centre, National Institute of Banking and Finance in Islamabad.
[***] Institute of Business Management Sciences, Faculty of Agricultural Economics and Rural Sociology, University of Agriculture, Faisalabad.

at PKR 1,148.871 billion in 2007/08. The major crops (wheat, rice, cotton, and sugarcane) contribute 34 percent, while 11 percent of the agricultural GDP is divided between minor crops. Horticultural crops (fruits, vegetables, and condiments) account for 76 percent of minor crops; fruits, which dominate horticultural crops, account for 59 percent of their total value (Pakistan, Ministry of Food, Agriculture and Livestock, 2008).

Mango exports are an important source of valuable foreign earnings for Pakistan. Exports increased from 1.16 thousand tonnes in 1975/76 to 105.21 thousand tonnes in 2006/07. The last five years have marked a massive increase in mango exports from Pakistan, which is generally attributed to increased access to traditional markets through improved shipping facilities, the rising number of Pakistani immigrants, and government policy[1] (Pakistan Horticulture Development and Export Board, 2005). Despite the increase in mango exports, however, its share in total mango production remains about 6 percent; this is lower than other leading mango exporters such as Mexico and Brazil, which account for 14 and 12 percent, respectively (Food and Agriculture Organization [FAO], 2007).

Mango exports from Pakistan are highly concentrated in a few markets. The major markets include the United Arab Emirates (UAE) and Saudi Arabia, where expatriate Pakistanis and Indians constitute the major customer base. Increased shipping facilities at cheaper rates, and relatively flexible and less stringent food safety requirements are some of the factors that explain the major share of mango exports to these markets. In 2006/07, 46 percent of the country's mango exports were shipped to the UAE alone, while Saudi Arabia, Oman, Kuwait, and Bahrain accounted for 17.61 percent, 12.79 percent, 1.55 percent, and 1.22 percent, respectively. Almost 76 percent of Pakistani mangoes are exported to three markets (the UAE, Saudi Arabia, and Oman). The UK is Europe's biggest market for total exports from Pakistan, accounting for about 11.46 percent, followed by France (1.48 percent) and Germany (1.22 percent) (Pakistan, Ministry of Food, Agriculture and Livestock, 2007).

Although Pakistan is a leading mango producer (FAO, 2007), it has been unable to reach its full potential as a mango exporter. Arguably, traditional methods of production, improper orchard management, poor post-harvest handling, traditional marketing practices, and lack of compliance with international market requirements have limited the

[1] These factors are important determinants of mango exports but were not included in this analysis due to the nonavailability of data. Our study was conducted to evaluate the impact of major factors on mango exports at the macro-level.

country's expansion of mango exports. Mangoes are perishable commodities that require careful handling during the export process. Controlled temperatures, durable packaging, and appropriate transportation are some of the important prerequisites that determine the fruit's freshness and shelf life. Infrastructure development and the availability of reefers (refrigerated transport) further enhance the marketing efficiency required for the export of this delicate fruit.

Other factors that affect mango exports from Pakistan include the relative profitability of selling mangoes in the international market; this is due to the price difference between national and international markets. Exporters often extend their market beyond national borders in the hope of obtaining higher prices for their product abroad. The domestic production of mangoes also influences the export process because it directly affects the exportable surplus. A good mango crop encourages exporters to sell their mangoes abroad whereas a poor crop rarely meets local requirements. The agricultural GDP of any country indicates the size of its market, which signals its attractiveness in the international market, whereas physical infrastructure is essential for exporting commodities, particularly perishables.

Given the importance of mangoes to Pakistan, there is a need to undertake a study that identifies the major determinants of the country's mango exports. This study seeks to identify some of the variables that influence the export of mangoes from Pakistan and to analyze and quantify the impact of the major determinants of the export process in order to devise a strategy to boost mango exports.

## 2. A Review of the Literature

Aujla, Abbas, Mahmood, and Saadullah (2007) investigate the constraints hindering the potential of Pakistan's fruit production and exports. The country's major share in returns from exports comes from the Middle East and Southeast Asia due to the relatively high quantities exported to these regions. Pakistan's inability to compete in the world's more expensive markets for horticultural products is explained by the nonavailability of infrastructure, the mismatch of Pakistan's fruits with the tastes and preferences of high-price markets, the high cost of refrigerated transport facilities and good-quality packing material, the lack of other inputs needed in processing, and credit constraints. These are important variables but are difficult to include in a quantitative analysis due to the nonavailability of specific data. Infrastructure, however, can be included by using a proxy variable such as the length of roads available.

Haleem (2005) investigates the export supply response of mangoes in Pakistan during 1975–2004, using Johansen's cointegration technique. The estimated export price elasticity for mangoes was 5.39, the domestic price elasticity was –6.73, and the domestic production elasticity was –2.16. The exchange rate elasticity remained 2.89. Although the study makes a sound attempt to evaluate the major determinants of mango exports from Pakistan at the macro-level, we prefer to use the relative price index instead of using domestic and export prices separately as independent variables. Haleem also finds the elasticity of mango production to be a little higher than in our study.

Haleem, Mushtaq, Abbas, and Sheikh (2005) examine the factors affecting citrus exports. These include domestic and export prices, national production, and foreign exchange rates. They use time-series data for the period 1975–2004, and employ cointegration and an error correction mechanism (ECM). The estimated export price elasticity is 1.48 while domestic price elasticity is –0.98. Among nonprice factors, the estimated elasticity of domestic citrus production, the exchange rate, and GDP are 1.37, 1.31, and 0.35, respectively.

Hassan and Ibnouf (2005) identify competitive capacity determinants (relative prices, relative stability of production, and efficiency of export practices) for Egyptian exports of certain fruits to the Saudi Arabian market, using time-series data for the period 1985–2000. They estimate multiple linear regression equations And their results indicate that the competitive capacity of Egyptian exports for these major fruits in the Saudi Arabian market could be increased by expanding the production of quality oranges and lemons, improving the efficiency of export processes, and reducing the cost of mango production while meeting product specifications and maintaining the relative stability of production. Although the study is country-specific, it helps to identify two major variables of the export model: the relative price index and the production status of the fruit in question.

Using time-series data for the period 1975–2003, Neef (2004) studies the export patterns for pears, apples, and strawberries from Belgium. The study finds that internal factors such as production and per capita availability play an important role in explaining variations in net exports, while external factors such as prices and foreign exchange rates appear to be less important. Tambi (1999) discusses factors that influence Cameroon's exports of cocoa, coffee, and cotton, applying a cointegration analysis. The combined short-run dynamic effect of lagged quantities of cocoa and coffee, the export/domestic price ratio, and GDP jointly explain changes in the export of cocoa, while lagged quantities of cocoa, coffee, and cotton do not seem to have significant short-run dynamic effects on changes in coffee exports.

Gunawardana, Kidane, and Kulendran (1995) estimate the export supply response of the Australian citrus industry using cointegration and error correction techniques. Their results show that, even in the long run, the supply of citrus exports is inelastic with respect to relative prices while domestic production capacity has a positive impact on export supply. The long-run price elasticity is found to be 0.73. Our findings are similar in that the relative price of mangoes has an inelastic impact on exports, while production capacity has a positive impact.

Reddy and Narayan (1992) assess the trade experience of Indian agriculture and the behavior of the net export supply functions for dominant commodities, i.e., rice, wheat, cotton, tobacco, sugar, jute, and tea, using autoregressive distributed lag formulations. They find that internal factors such as production and per capita availability play an important role in explaining variations in net exports, while external factors such as prices and foreign exchange rates are less important.

Islam (1990) identifies various factors affecting horticultural exports from developing countries, including GDP, the exchange rate, production, and social and physical infrastructure, and calculates the effect of these variables by estimating regressions in logarithmic form. In the first model, production, GDP, the real exchange rate, and the index of trade dependence are found to significantly affect exports. In the second model, GDP is replaced by two variables representing physical and human infrastructure, both of which are found to be significant. The share of manufacturing exports in total exports is also found to have a significant positive effect. The study calculates the price and income elasticities for the demand and supply of horticultural exports: –0.71, 0.74, and 1.08, respectively. It also helps to identify an important variable, i.e., GDP, which can be used to capture the effect of market size.

The literature review highlights two important points. First, it supports the use of cointegration to analyze time-series data; second, it helps to identify the major variables determining the export of perishable commodities at the macro-level. As mentioned earlier, this study was conducted to evaluate the impact of major variables (domestic production, GDP, infrastructure, and the relative price index) on mango exports from Pakistan using cointegration and ECM techniques.

## 3. Conceptual and Empirical Framework

We estimate the export supply response of mangoes using cointegration and ECM techniques applied to secondary data for the period 1970–2005,[2] collected from various sources including the FAO database, and various issues of the *Pakistan Economic Survey* and *Pakistan Statistical Year Book*. Johansen's approach is used to test for cointegration between mango exports and its explanatory variables, and the ECM is used to estimate short- and long-run elasticities. The Granger causality test is conducted to determine the direction of causation between variables to draw policy conclusions.

### 3.1. Empirical Model

The specific form of the mango export supply function is:

$$\ln Ex_t = \gamma_0 + \gamma_1 \ln RP_t + \gamma_2 \ln P_t + \gamma_3 \ln G_t + \gamma_4 \ln RD_t + \gamma_5 DS_t + \mu_t \quad (1)$$

$Ex_t$ represents mango exports (in thousand tonnes), $Rp_t$ is the index of relative prices of mango exports (1999/2000 = 100), $P_t$ represents domestic mango production (in thousand tonnes), $G_t$ is real agricultural GDP measured at a constant factor cost of 1999–2000 (in million rupees), $Rd_t$ represents the length of all-weather roads (in thousand kilometers) as a proxy variable for infrastructure, $DS$ is a dummy variable used to capture the effect of international standardization, and $\mu_t$ is a stochastic error term.

### 3.2. Data Sources and Variable Specification

The sources of data, the rationale for choosing specific variables, and their construction are discussed below.

[2] The data was collected from the FAO database, which provides data on mango exports and value till 2005 beyond which the data on mangoes is combined with that on guavas and mangosteen.

### *3.2.1. Mango Exports*

This variable is taken as a dependent variable and regressed against domestic mango production, the index of relative prices, real agricultural GDP, the length of all-weather roads, and international standardization. For this purpose, data on mango exports was taken from the FAO's (2007) database and measured in thousand tonnes.

### *3.2.2. Mango Production*

The level of domestic production is considered important because it determines the volume available for export purposes. This is particularly important for developing countries where exportable surplus is generated after local requirements have been met. A good crop harvest will increase the probability of exporting more of that commodity. The domestic production of mangoes was identified as one of the major determinants of exports from Pakistan. Data on this variable was obtained from the FAO's (2007) database and measured in thousand tonnes.

### *3.2.3. Index of Relative Prices*

The index of relative prices of mango exports is calculated as follows, using 1999/2000 as the base year:

$$RP_t = \frac{PXIN}{PDIN} \times 100$$

where *RP* is the index of relative prices of mango exports, *PXIN* is the index of the Pakistani rupee price of mango exports, and *PDIN* is the index of the domestic wholesale price of mangoes.

This variable indicates the relative profitability of selling in export markets over that of selling in domestic markets. The index of national prices of mangoes is constructed using 1999/2000 as the base year. The index of export prices is calculated in the same way.

The data for this purpose was taken from the FAO's (2007) database. Data on domestic wholesale prices was taken from various issues of the Pakistan Bureau of Statistics' *Pakistan Statistical Year Book*. These prices were then used to construct a national average price for mangoes. Data on the export value of mangoes was obtained from the FAO's (2007) database in thousand dollars per tonne. The export prices of mangoes were calculated by dividing their export value by the export quantity for each year and converted into thousands of rupees at the official exchange rate.

#### *3.2.4. Real Agricultural GDP*

A country's agricultural GDP indicates the size of its market and level of economic growth in the agriculture sector. A country with a high agricultural GDP may be a good performer, making it an active exporter in the international market. For the purposes of this study, we calculated the agricultural GDP at constant factor cost (in PKR million) for each year, and divided it by the GDP deflator for that year to convert each value into real terms. Data on agricultural GDP and the GDP deflator was obtained from the State Bank's Economic Bulletins.

#### *3.2.5. Infrastructure Development (All-Weather Roads)*

Governments invest in developing infrastructure because it affects both the quality and quantity of agricultural produce by enhancing the link between production and consumption. In empirical research, determining an accurate and exact variable, such as infrastructure development, can be difficult. Although we considered the use of variables such as storage capacity, processing units, and the quantity of mangoes transported from farms to processing factories to capture the effect of infrastructure development, data for these variables was not available. Accordingly, we have used a proxy variable to capture the effect of infrastructure development on mango exports, i.e., the length of all-weather (metalled) roads. Data on all-weather roads (in kilometres) was taken from various issues of the *Pakistan Economic Survey*.

#### *3.2.6. International Standardization (Dummy Variable)*

A dummy variable was used to capture the effect of international standardization—i.e., the implementation of World Trade Organization (WTO) agreements—on the export of mangoes from Pakistan. The variable was constructed by assigning a value of 0 to years prior to the implementation of WTO agreements and 1 to years thereafter.

### ***3.3. Johansen's Cointegration Approach***

In dealing with secondary data, classical regression analysis assumes that time-series data is stationary, but that most time series trend over time, which, if regressed, may be spurious (Granger & Newbold, 1974). Time-series data is said to be stationary if its mean, variance, and covariance are constant over time (Gujarati, 1995). Thus, before undertaking our analysis, we test the data series for the presence of any unit roots, i.e., for nonstationarity using the augmented Dickey-Fuller (ADF) test as follows:

$$\Delta Y_t = \alpha_3 + \beta_3(\phi_3 - 1)Y_{t-1} + \sum_{i=1}^{k} \theta_i \Delta Y_{t-i} + \mu_t \quad (2)$$

where $Y_t$ is the series under consideration and $\mu_t$ is assumed to be an identically and independently distributed random variable. The ADF test determines statistically the null hypothesis that the time series of the given variables has a unit root against the alternative hypothesis of a stationary time series (Dickey & Fuller, 1981).

The concept of cointegration was introduced by Granger (1981, 1983) and statistically analyzed by Engle and Granger (1987). In the literature, there are two major approaches to testing for cointegration: the residuals-based ADF approach proposed by Engle and Granger (1987) and Johansen's full information maximum likelihood approach (Johansen, 1988; Johansen & Juselius, 1990). The Engle and Granger approach entails testing for cointegration and then using residuals in an ECM to obtain information on the speed of adjustment in the long run. The major weaknesses of this approach, however, include its low power and finite sample bias. It cannot be used in a situation where there are more than two variables (Dolado, Jenkinson, & Sosvilla-Rivero, 1991; Charemza & Deadman, 1992), making Johansen's approach preferable. The following vector autoregressive (VAR) model forms the basis of the multivariate cointegration of Johansen's maximum likelihood approach (Johansen & Juselius, 1990):

$$Z_t = A_i Z_{t-1} + \ldots\ldots + A_k Z_{t-k} + \mu_t \quad (3)$$

where $Z_t$ is an ($n$ x 1) vector of $I$(1) variables with both endogenous and exogenous variables, $A_i$ is an ($n$ x $n$) matrix of parameters, and $\mu_t$ is an ($n$ x 1) vector of white noise errors. Each equation in (3) can be estimated using ordinary least squares (OLS) because each variable in $Z_t$ is regressed on lagged values of its own and all other variables in the system. Since $Z_t$ is assumed to be nonstationary, it is convenient to rewrite equation (3) in its first difference or error correction form (Cuthbertson, Hall, & Taylor, 1992) as

$$\Delta Z_t = \Gamma_i \Delta Z_{t-1} + \ldots\ldots\ldots + \Gamma_{k-1} \Delta Z_{t-k+1} + \Pi Z_{t-k} + \mu_t \quad (4)$$

where

$$\Gamma_i = -(I - A_1 - A_2 - \ldots . A_i), (i = 1, \ldots\ldots, k-1), \text{ and}$$
$$\Pi = -\left(I - A_1 - A_2 -, \ldots, -A_k\right)$$

The specification above provides information on the short-run and long-run adjustments to the changes in $Z_t$ by estimating $\Gamma$ and $\Pi$, respectively. The term $\Pi Z_{t-k}$ gives information on the long-run equilibrium relationship between the variables, while information about the number of cointegrating relationships among the variables in $Z_t$ is given by the rank of the matrix $\Pi$. If the rank of the matrix $\Pi$ is $0 < r < n$, there are $r$ linear combinations of the variables in $Z_t$ that are stationary.

Here, the $\Pi$ matrix can be decomposed into two matrices, $\alpha$ and $\beta$, such that $\Pi = \alpha\beta$, where $\alpha$ is the error correction term measuring the speed of adjustment in $\Delta Z_t$, and $\beta$ contains $r$ distinct cointegrating vectors, i.e., the cointegrating relationship between the nonstationary variables. The model may have some variables that are $I(0)$ and are insignificant in the long-run cointegrating space but that affect the short-run model. In this case, equation (4) can be written as:

$$\Delta Z_t = \Gamma_i \Delta Z_{t-1} + \Pi Z_{t-k} + \psi D_t + \mu_t \tag{5}$$

where $D_t$ represents the $I(0)$ variable, which is often included to take account of short-run shocks to the system, such as policy interventions.

Johansen and Juselius (1990) use two likelihood ratio tests—trace and maximum eigenvalue tests—to determine the cointegration rank and estimate the long-run parameter matrix. The trace test is based on the stochastic matrix and is defined as:

$$\lambda_{trace} = -2 \ln Q = -T \sum_{i=r+1}^{p} \ln(1 - \lambda_i) \tag{6}$$

The null hypothesis of this test is that the number of distinct cointegrating vectors is less than or equal to $r$ (i.e., no cointegrating vector) against the alternative that $r > 0$ (i.e., one or more cointegrating vectors). The maximum eigenvalue test, used to detect the presence of a single cointegrating vector, is based on the following:

$$\lambda_{\max} = -2 \ln(Q : r | r+1) = -T \ln(1 - \lambda_{r+1}) \tag{7}$$

This statistic tests the null hypothesis that the number of cointegrating vectors is *r*, against the specific alternative of (*r* + 1) cointegrating vectors. The distribution of these statistics depends on the number of nonstationary components (i.e., the number of variables we are testing for cointegration) defined by (*n* – *r*). The Monte Carlo derivation of critical values for these tests has been simulated and tabulated by Johansen (1988) and Osterwald-Lenum (1992). Harris (1995) considers the trace test to be more powerful.

The Granger representation theorem states that, if a set of variables is cointegrated, this implies that the residual of the cointegrating regression is of order *I*(0); thus, there exists an ECM describing this relationship. The theorem explains that cointegration and an ECM can be used as a unified theoretical and empirical framework to analyze both short- and long-run behavior. If the series $Y_t$ and $X_{it}$ are *I*(1) and cointegrated, then the ECM is represented in the following form:

$$\Delta X_{it} = \alpha_0 + \sum_{t=1}^{n} \beta_i \Delta X_{(t-1),i} + \sum_{t=1}^{n} \beta_j \Delta X_{(t-1),j} + \delta ECT_{t-1} + \mu_t \tag{8}$$

$$\Delta X_{jt} = \varphi_0 + \sum_{t=1}^{n} \sigma_j XP_{(t-1),j} + \sum_{t=1}^{n} \sigma_i X_{(t-1),i} + \lambda ECT_{t-1} + \varepsilon_t \tag{9}$$

where Δ is the difference operator, $X_{it}$ is the mango export series (*i* = 1), and $X_{jt}$ represent the independent variables mentioned earlier (*i* = 2 ... 5). $\mu_t$ and $\varepsilon_t$ are white noise error terms, $ECT_{t-1}$ is the error correction term (adjustment vector) derived from the long-run cointegrating relationship, and *n* represents the optimal lag length orders of the variables that are determined using the general-to-specific modeling procedure (Hendry & Ericsson, 1991). The null hypotheses are: $X_{it}$ will Granger-cause $X_{jt}$ if $\mu_t \neq 0$. Similarly, $X_{jt}$ will Granger-cause $X_{it}$ if $\varepsilon_t \neq 0$. To apply the Granger causality test, we calculate the F-statistics under the null hypothesis that, in the above equations, all the coefficients of $\mu_t$ and $\varepsilon_t$ are equal to 0.

## 4. Results and Discussion

The analysis was conducted in three steps. First, the ADF test was used to test for the presence of unit roots in the variables. Next, Johansen's full information maximum likelihood approach was used to test the long-run relationship between variables and an ECM was employed to obtain short-run elasticities. Finally, the direction of causation between variables was tested using the Granger causality test.

### *4.1. Test for Stationarity (Unit Root Test)*

The null of the unit root is tested against the alternative hypothesis of stationarity by the ADF regressions, first by including an intercept but not a trend, and then by including both an intercept and a linear trend. The maximized log-likelihood, Akaike information criterion (AIC), and Schwarz Bayesian criterion (SBC) are used to determine the optimal lag length of the augmented terms. The computed absolute value of the test statistic (Dickey-Fuller statistic) is checked against the maximum values of these criteria applying a 95 percent absolute critical value for the ADF statistic. If the computed absolute test statistic value is greater than the absolute critical value, we can reject the null of the unit root, which implies that the time series is stationary. On the other hand, if the absolute test statistic value is less than the absolute critical value, then we accept the null of the unit root, implying that the series is nonstationary.

The variable of mango exports (LEx) is tested for the presence of a unit root using the ADF test. The computed absolute value for the nontrended model is –0.73, which is far smaller than the 95 percent absolute critical value for the ADF statistic. The computed absolute value for the trended model is –2.38, which again falls below the 95 percent absolute critical value for the ADF statistic. Both these tests confirm that the data series on mango exports is nonstationary. The other variables are also tested for the presence of a unit root and found to be nonstationary (Table 1).

**Table 1: Results of unit root test**

| Variable | Nontrended model | Trended model | $\varphi_3$ |
|---|---|---|---|
| LEx | -0.73 | -2.38 | 5.80 |
| LRp | -2.81 | -2.78 | 6.16 |
| LP | -0.29 | -3.37 | 2.86 |
| LG | -0.25 | -2.64 | 4.47 |
| LRd | -1.97 | -0.53 | 0.46 |
| Critical value | -2.93 | -3.50 | 6.73 |

***Source:*** Authors' calculations.

The next step is to confirm our results by checking for the presence of a unit root in the first difference of these data series. All the data series are found to be *I*(1) (Table 2).

**Table 2: Results of unit root test for first-difference series**

| Variable | Nontrended model | Trended model |
|---|---|---|
| LEx | -5.50 | -5.42 |
| LRp | -5.85 | -5.73 |
| LP | -4.50 | -4.48 |
| LG | -6.30 | -6.19 |
| LRd | -3.96 | -3.67 |
| Critical value | -2.97 | -3.58 |

***Source:*** Authors' calculations.

### *4.2. Testing for Cointegration*

After testing for unit roots in the given data series, we estimate the cointegrating regression between the variables to determine their long-run relationship. In the first stage, we identify the order of the VAR model using the adjusted likelihood ratio (LR) test and the AIC and SBC with a maximum of four lags. The results for the selection of the order of the VAR model identifies order 1 against the SBC's largest value. The AIC does not support this result; its largest value suggests the order of 3 for the VAR model. However, the final selection is made on the basis of the adjusted LR test, which confirms the SBC's suggested order since the adjusted LR test value became insignificant for the first time at the order of 1. Thus, the selected order of the VAR model for our mango export supply response model is estimated to be 1 (Table 3).

**Table 3: Selecting the order of the VAR model**

| Order | AIC | SBC | Adjusted LR test |
|---|---|---|---|
| 3 | 181.04 | 103.60 | - |
| 2 | 163.79 | 112.17 | 47.06 (0.10) |
| 1 | 167.80 | 141.99 | 85.56 (0.94) |
| 0 | 130.88 | 130.88 | 236.71 (0.00) |

Note: AIC = Akaike information criterion, LR = likelihood ratio, SBC = Schwarz Bayesian criterion. Values in parentheses are p-values.
***Source:*** Authors' calculations.

We then test for the presence and number of cointegrating vectors in the model's series. The rank of cointegration, i.e., the number of cointegrating vectors, is selected using maximum eigenvalues and trace value test statistics. For this purpose, there are three possible models[3] but based on a set of model fitness criteria, we select and explain the second model. Based on the maximum eigenvalue test statistics, the hypothesis of no cointegration is rejected and the alternative hypothesis of the existence of cointegration in the series is accepted: the results of the maximum eigenvalues test show that values are significant at 5 percent for the first test statistics because the first statistical value for the test is greater than the 95 percent critical value. According to Harris (1995), the number of cointegrating vectors is one when the null hypothesis is rejected for the first time. Thus, on the basis of these results, we can safely assume that there is one cointegrating vector in the series (Table 4).

**Table 4: Cointegrating LR test based on maximum eigenvalues of stochastic matrix**

| $H_o$ | $H_A$ | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| R = 0 | $r = 1$ | 69.61 (40.53) | 47.26 (39.83) | 52.92 (43.61) |
| R ≤ 1 | $r = 2$ | 27.30 (34.40) | 18.05 (33.64) | 25.82 (37.86) |

Note: *r* is the number of cointegrating vectors; 95 percent critical values are given in parentheses.
***Source:*** Authors' calculations.

The results of the trace test confirm the results obtained using maximum eigenvalues, yielding one cointegrating vector because the test shows that the values are significant at 5 percent for the first test statistics since the first statistic value for the tests is greater than the 95 percent critical value. Thus, in the case of both tests, we reject the possibility of two cointegrating vectors and assume one cointegrating vector in the series (Table 5).

[3] Model 2: Cointegration with restricted intercepts and no trends in the VAR. Model 3: Cointegration with unrestricted intercepts and no trends in the VAR. Model 4: Cointegration with unrestricted intercepts and restricted trends in the VAR.

**Table 5: Cointegrating LR test based on trace values of stochastic matrix**

| $H_o$ | $H_A$ | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| R = 0 | $r \geq 1$ | 148.87 (102.56) | 95.96 (95.87) | 116.18 (115.82) |
| R ≤ 1 | $r \geq 2$ | 69.25 (75.98) | 48.00 (70.49) | 61.26 (87.17) |

Note: *r* is the number of cointegrating vectors; 95 percent critical values are given in parentheses.
***Source:*** Authors' calculations.

### *4.3. Johansen's Normalized Estimates and ECM Estimates*

In our estimation of an ECM for mango exports, we include the same number of lags as for the unit root and cointegration tests, i.e., four lags. The parameters of the Johansen cointegration regression are the estimates of the long-run elasticities whereas the coefficients of the difference terms in the ECM are the estimates of the short-run elasticities.

The relative price index variable shows the relative profitability of selling mangoes in export markets compared to local markets. This variable is significant both in the short and long run—their t-values are 3.43 and 2.50, respectively (Table 6). This shows that the variable is significant at a 1 percent and 5 percent level of confidence, respectively. The variable's direction in the short run as well as in the long run is also consistent—it has a positive sign relative to mango exports, which implies that relative price rises in the export market increase mango exports from Pakistan because this increases the relative profitability linked with the price increase.

The variable's elasticity coefficient in the short run indicates that a one-percent increase in the relative price index leads to a 0.36 percent increase in mango exports from Pakistan. The elasticity coefficient increases up to 0.55 in the long run, which implies that a one-percent increase in the relative price index introduces a 0.55 percent increase in mango exports. A larger long-run elasticity coefficient for mango exports with respect to the relative price index is logical because mango crops require an additional year to respond to any price changes; in the case of a quantum response by domestic mango production to rising international prices, it may be necessary to grow an entirely new crop, which could take several years. So, mango exports are more responsive to the relative price index in the long run than the short run.

The mango production variable provides a base for developing a strong export culture for mangoes in Pakistan. The t-values for mango production in the short and long run are 2.64 and 1.58, respectively, which show that the variable is significant at a 5 percent level of confidence in the short run and at a 10 percent level of confidence in the long run (Table 6). The variable's direction in the short and long run is also consistent because it has a positive sign in relation to mango exports. This implies that an increase in mango production enhances the level of mango exports from Pakistan.

The variable's elasticity coefficient in the short run indicates that a one-percent increase in mango production leads to a 2.87 percent increase in mango exports from Pakistan. The elasticity coefficient falls to 1.43 in the long run, implying that a one-percent increase in mango production introduces a 1.43 percent increase in mango exports. The smaller elasticity coefficient in the long run indicates an absence of export planning for mangoes. It is also clear that Pakistan has not capitalized on its potential for increasing exports over time.

The real agricultural GDP variable indicates the pace of relative economic growth and market size in Pakistan. The variable is significant both in the short and long run—their t-values are both 1.83 (Table 6). This shows that the variable is significant at a 10 percent level of confidence both in the short and long run. The variable's direction in the short and long run is also consistent since it has a positive sign in relation to mango exports, implying that growth in real agricultural GDP increases mango exports from Pakistan. As mentioned in Section 3, agricultural GDP indicates the relative size of the economy as well as its stage of development. A well-developed economy, denoted by the value of its agricultural GDP, will be suited to exporting agricultural commodities.

Pakistan, an agriculture-based economy, is a case in point. The elasticity coefficient for this variable in the short run indicates that a one-percent increase in real agricultural GDP leads to a 0.97 percent increase in mango exports from Pakistan. The elasticity coefficient rises to 1.03 in the long run, implying that a one-percent increase in real agricultural GDP introduces a 1.03 percent increase in mango exports. So, mango exports are more responsive to real agricultural GDP in the long run than in the short run.

The impact of infrastructure development on mango exports is assessed using the length of all-weather roads as a proxy variable. In Pakistan, the road network can be divided into two categories, i.e., all-weather roads, which are metalled links between urban and rural areas, and low-type roads, which are not useable in the rainy season. This variable is insignificant in the short run and significant at a 10 percent level of confidence in the long run—the t-values for the short run and long run are 0.40 and 1.93, respectively (Table 6).

The variable's direction both in the short and long run is also consistent; it has a positive sign in relation to mango exports, which implies that an increase in the length of all-weather roads increases mango exports from Pakistan. The variable's elasticity coefficient in the short run indicates that a one-percent increase in the length of all-weather roads leads to a 0.55 percent increase in mango exports; the elasticity coefficient rises to 0.56 in the long run, implying that a one-percent increase in the length of all-weather roads introduces a 0.56 percent increase in mango exports. So, mango exports are slightly more responsive to infrastructure development in the long run than in the short run.

A dummy variable is used to determine the impact of international standardization, i.e., WTO agreements. This variable is insignificant in the long run but significant at a 10 percent level of confidence in the short run.

The coefficient of the error correction term has a negative sign, which corresponds to theory and explains the adjustment process and speed of adjustment from any short-run shock toward long-run equilibrium. The error correction term is –0.52, which is highly significant, suggesting that 52 percent of any disequilibrium in the short run will adjust in the unit time period (one year in this case). This means that any short-run adjustment will be fully compensated for in almost less than two years.

**Table 6: Estimated long- and short-run elasticities**

| | Short run | | Long run | |
|---|---|---|---|---|
| **Regressor** | **Elasticity** | **t-value** | **Elasticity** | **t-value** |
| Constant | 0.29 | 2.03** | 25.70 | 1.13 |
| LRp | 0.36 | 3.43*** | 0.55 | 2.50** |
| LP | 2.87 | 2.64** | 1.43 | 1.58* |
| LG | 0.97 | 1.83* | 1.03 | 1.83* |
| LRd | 0.55 | 0.40 | 0.56 | 1.93* |
| DS | 0.17 | 1.96* | 0.55 | 1.34 |
| Ecm1(-1) | -0.528 | -4.28*** | | |
| Diagnostic tests | | | | |
| $R^2$ | 0.67 | Jarque-Bera normality-$\aleph^2$ | | 0.614 |
| DW statistics | 1.92 | Wald test-$\aleph^2$ | | 0.159 |
| LM-$\chi^2$ | 3.44 (0.20) | RESET-$\aleph^2$ | | 0.935 |

Note: *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.
***Source***: Authors' calculations.

All the diagnostic tests conducted in this analysis yield satisfactory results, which confirm the authenticity of the estimation process and estimates. The Lagrange multiplier (LM) test indicates that there is no problem of serial correlation among the residuals since the computed value is greater than 0.05 and we can reject the null of serial correlation among the residuals. The Ramsey regression equation specification error test (RESET) also verifies the correct functional form of the model. The Jarque-Bera test confirms the normal distribution of the residuals. The Wald test provides the significance level supporting the ECM over the partial adjustment specification. The $R^2$ value indicates that about 67 percent of the variation in mango exports is explained by the independent factors included in the model. The Durban-Watson statistics also verify that there is no serial correlation among the residuals (Table 6).

### *4.4. Granger Causality Test*

Granger causality assumes that information relevant to the prediction of the variables in question is contained solely in the time-series data. Here, causality refers to the direction of cause from one variable to the other, which is regressed separately on each other (Gujarati, 1995). Once we have determined the short- and long-run relationships between the variables, it is also useful to determine the direction of cause between them.

We run separate regressions for each of the explanatory variables, which are of *I*(1) with the dependent variable mango exports, including an error correction term, and determine the Granger causality. First, we regress mango exports (LEx) and real agricultural GDP (LG) separately on each other. The results suggest unidirectional causality from real agricultural GDP (LG) to mango exports (LEx) since the estimated F-statistic (6.01) and respective P-values are significant (Table 7). There is no reverse causation from mango exports (LEx) to real agricultural GDP (LG) since the computed F-statistic (0.85) is not statistically significant. The agricultural GDP of a country shows its growth pattern and market size, so it seems logical that real agricultural GDP should affect mango exports. However, the share of mango exports in agricultural GDP is not large enough to lead to a causative change from mango exports (LEx) to real agricultural GDP (LG).

Next, the causative relationship between mango exports (LEx) and the relative price index (LRp) is determined by regressing each separately on the other. The results suggest bi-directional or bilateral causality between the two variables. In the first case, the estimated F-statistic (6.04) and P-value are significant, implying that the relative price index (LRp) Granger-causes a change in mango exports (LEx). Similarly, there is reverse causation from mango exports (LEx) to the relative price index (LRp) since the F-statistic (12.83) is again statistically significant (Table 7). The relative price index (LRp) shows the relative profitability of selling mangoes in the local market as against the international market, so as a policy implication, this variable should cause a change in mango exports. Conversely, mango exports might not be independent of the relative price index because price is one of its most important determinants.

In determining the causative relationship between mango exports (LEx) and mango production (LP), the results suggest unidirectional causality from mango production (LP) to mango exports (LEx) since both the estimated F-statistic (4.64) and respective P-values are significant. There is no reverse causation from mango exports (LEx) to mango production (LP) since the computed F-statistic (0.78) is not statistically significant (Table 7). Mango production is the basis for exports, and so it Granger-causes mango exports, but this is not applicable in reverse because mango exports constitute a small proportion of the total mango production in Pakistan and there is apparently no difficulty in obtaining an exportable surplus for export. There is, therefore, only unidirectional causation between these two variables.

Finally, we determine the causative relationship between mango exports (LEx) and all-weather roads (LRd) (the proxy variable for physical infrastructure) by regressing both separately on each other. The results suggest bi-directional or bilateral causality since both the estimated F-statistic (4.55) and respective P-values are significant (Table 7). This implies that all-weather roads (LRd) Granger-cause a change in mango exports (LEx). Similarly, there is reverse causation from mango exports (LEx) to all-weather roads (LRd) since the computed F-statistic (3.49) is again statistically significant. Physical infrastructure is one of the basic requirements of enhancing the quality of the domestic marketable surplus, which further acts as a primary source for generating exportable commodities. Bi-directional causality between these two variables is, therefore, a logical outcome.

**Table 7: Results of Granger causality test from ECM**

| Causality | F-statistics | P-value | Direction |
|---|---|---|---|
| LG→LEx | 6.01 | 0.003* | Unidirectional |
| LEx→LG | 0.85 | 0.47 | |
| LRp→LEx | 6.04 | 0.003* | Bi directional |
| LEx→LRp | 12.83 | 0.01* | |
| LP→LEx | 4.64 | 0.01* | Unidirectional |
| LEx→LP | 0.78 | 0.51 | |
| LRd→LEx | 4.55 | 0.01* | Bi directional |
| LEx→LRd | 3.49 | 0.03* | |

* Significant.
***Source*:** Authors' calculations.

## 5. Recommendations

Our findings show that the highest elasticity coefficient in the short and long run is found for mango production followed by real agricultural GDP. In this context, improving the production potential of mangoes would be a good initiative to enhance their export from Pakistan. Mango growers should be trained in the scientific management of their orchards. Policies conducive to boosting agricultural GDP are also advisable, in which connection investment in agriculture, particularly to add value to the exportable surplus, would be a good policy direction to take.

Infrastructure is a prerequisite for boosting exports by developing a link between production areas and terminal markets. Mangoes are locally transported in trucks since refrigerated reefers are limited. The road network in Pakistan has improved but many roads are still not in good condition. There should be greater investment in the provision of refrigerated reefers; at the same time, a network of motorways should be established across Pakistan linking production and terminal markets. Our findings, in which road length has been used as a proxy variable for infrastructure, show that it significantly affects mango exports both in the short and long run.

Another important finding is the significant and positive impact of sale price on mango exports. Currently, mangoes from Pakistan are considered a low-price product in various export markets. Most exporters target traditional low-value markets. Another important requirement for exporting mangoes from Pakistan on a sustainable basis is compliance with international standardization such as WTO agreements. In this context, we recommend adopting an integrated, uniform effort (through the mutual cooperation of the private and public sectors). In addition, greater marketing efforts are needed to develop a better image of Pakistani mangoes by arranging seminars, workshops, and mango festivals in Pakistan.

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# The Impact of Health Information Provision on Breast Cancer-Related Knowledge and Protective Behaviors: An Experiment in Health Education

**Sarah Shahed***

**Abstract**

*This study examines the impact of health information provision on health-related knowledge and corresponding behaviors. Our main assumption is that women's health can be improved by adopting health protective and health-enhancing behaviors. The study employs a before–after, no-control-group design, aimed at examining whether exposure to health knowledge concerning breast cancer can change participants' behavior in relation to breast self-examination. Our sample consists of 50 young females whose knowledge and behavior related to breast cancer was assessed in a pre-exposure phase, followed by an exposure session during which they were shown a video film, participated in a discussion, and were given health education literature about breast cancer to take home. Two weeks later, the participants were reassessed, using the same measures. Their health knowledge and behavior were found to have improved significantly. We recommend that formal education should incorporate health education as part of the curricula at all academic levels, especially for women. The mass media can also play an important role in improving public health protective behavior.*

**Keywords**: Health, breast cancer, behavior, Pakistan.

**JEL classification**: I10.

## 1. Introduction

Individual awareness is key to promoting health, preventing disease, encouraging medical consultation, or taking prompt health-directed action. People can be expected to take health-enhancing actions only when they are aware of the difference between healthy and unhealthy lifestyles. In a culture that places a high value on fatty foods, where overweight people are considered "fortunate", and domestic labor is abundant, promoting the concept of healthy habits would mean changing a generations-old system of cultural norms. Many modern diseases are,

* Professor, Applied Psychology and Director of Women Institute of Leadership and Learning, Lahore College for Women University, Lahore, Pakistan.

however, lifestyle-related, and so it becomes imperative to modify health habits. This is even more significant in the case of diseases such as various forms of cancer, including breast and testicular cancers, which can be detected conveniently at a very early stage.

Studies conducted over the last five to ten years indicate that breast cancer is the most common form of cancer among females in Pakistan. An estimated one third of all malignant cases are patients of breast cancer, and Pakistan has the highest incidence of breast cancer in Asia (Aziz, Sana, Akram, & Saeed, 2004). According to some estimates, there are 30,000 new cases of breast cancer in Pakistan every year (Bhurgri et al., 2003; World Health Organization & Pakistan, Ministry of Health, 2004). The likelihood that a Pakistani woman will develop breast cancer is 1 out of 9. The incidence of breast cancer in Pakistan is much higher than that in India— 50/100,000 versus 19/100,000—despite the two countries' similar socio-cultural conditions (Naeem, Nasir, Aman, Ahmad, & Samad, 2008; Sohail & Alam, 2007).

An important aspect to consider is the disease's early presentation. Whereas breast cancer presents itself at around 60 years in the West, it has been recorded at lower ages in Pakistan (Mahmood, Rana, & Ahmad, 2006; Naeem, Khan et al., 2008). Taj, Akbar, Hassan, and Yusuf (2009) report the mean age to be 33 years in their prospective descriptive study of 200 female breast cancer patients—the age range is an alarming 14 to 71 years. The average age of presentation in this study is much lower than that reported in other studies. Naeem et al. (2008) report the mean age to be 48.3, with an age range of 32 to 75 years.

Recent indigenous investigations have revealed another even more alarming fact—the high frequency of females reporting for a delayed diagnosis with mature malignancy. This becomes an issue that requires special attention because breast cancer can be detected at a very early stage, even without medical assistance, and an early detection would mean a very good prognosis. The problem becomes complex when patients are relatively young but report for medical diagnosis at a late stage when treatment may not produce the desired outcomes (Mamoon, Sharif, Mushtaq, Khadim, & Jamal, 2009).

A recent study shows that 72 percent of a total of 200 female breast cancer patients investigated at Rawalpindi General Hospital reported for diagnosis at Stage III or IV of the malignancy. The majority of the sample was completely ignorant about the disease. Few (12 percent) were fully aware and one fourth of patients were partially aware. Around 92 percent were unaware of the significance of breast self-examination (BSE). On average, women had taken 10 months to self-discover the lump and report it to their doctor. Considering the delayed medical consultation and level of awareness about breast cancer, the study's authors emphasize the need to improve people's awareness level (see Taj et al., 2009).

Health knowledge and awareness can play a significant role in the practice of health behaviors. People are more likely to seek medical consultation for symptoms, provided they know what their symptoms might represent. Carelli et al. (2008) highlight the importance of disseminating health-related knowledge and its relationship with the performance of specific health behaviors. They find that the mass media is the most significant—although not necessarily the most accurate—source of knowledge about BSE for the sample of women included in their study, followed by "medical sources". In a study on Turkey, Avci (2008) finds that, out of a sample of 103 Muslim females, only 26.2 percent were aware of the practice of BSE and an even smaller minority of 4.3 percent actually performed it.

Using a sample of 489 elderly patients in the Midwest in the US, Cho, Lee, Arozullah, and Crittenden (2008) explore the links between health status, the utilization of health services, and health literacy. They argue that increasing health literacy may be an effective way of improving health status, particularly among older patients.

This study was conducted to examine the impact of health information provision on young females' health-related knowledge and practices. It was designed following a within-subjects, before–after, no-control-group design to test two hypotheses:

1. If women are provided health-related information, their scores for health knowledge measures will increase.
2. If women are provided health-related information, their scores for health behavior measures will increase.

## 2. Methodology

### *2.1. Sample*

Our sample consisted of 50 final-year female graduates enrolled at the Lahore College for Women University, all studying gender and development studies. The respondents were sampled from the same university and class to ensure they had a similar academic background and had been exposed to the same kind of stimulation over the last four years. Their age ranged from 18 to 21 years. All were day scholars who lived in Lahore, and whose families had a monthly income ranging from PKR 15,000 to 25,000.

### *2.2. Materials*

The following measures were used in this study.

- **Health knowledge questionnaire**. The questionnaire, given in English, comprised 28 items and was developed specifically for this study. Twenty-one items pertained to breast cancer-related knowledge, while the remaining seven covered respondents' health behavior.
- **Multimedia CD about cancer**. We used a commercially available CD titled "Breast cancer: The essential breast cancer reference", prepared by John H. Fetting and six other colleagues. Participants were shown a series of 35-minute-long clips of the CD during the treatment/exposure phase of the study.
- **Health education leaflet about breast cancer**. A leaflet about breast cancer was developed for this study.
- **Health education talk and discussion on cancer**. Participants were also given a health education talk about cancer with special reference to breast cancer. The talk focused primarily on cancers more commonly found in females and the significance of early detection, especially in the case of breast cancer.

### *2.3. Procedure*

Prior to the study, a discussion was held with the participants in order to assess whether they had been recently exposed to cancer-related information. As mentioned earlier, they all came from similar backgrounds, and none reported having had any previous exposure to breast cancer-related information, whether in print or electronic form.

The study was conducted in three phases. The first phase was the pre-treatment phase in which the health knowledge questionnaire was used to develop a baseline assessment of participants' breast cancer-related knowledge and behavior. The second phase followed at the same venue after a half-hour break. In this session, participants were shown the video CD on health education, followed by a talk and discussion about cancer. At the end of the session, health education leaflets were distributed among the participants to take home. The third phase was held a fortnight after the first two. The same group of participants was invited to the same venue, and their health knowledge and health behaviors were measured once again.

## 3. Results

Table 1 presents a brief description of some of the personal characteristics of the respondents in our sample. Since the sample was selected keeping in view the study's basic goal, i.e., to bring about a change in respondents' health knowledge and health behavior, they were selected on the basis of similar educational and family backgrounds and their lack of prior exposure to cancer-related information. Respondents fall within a very narrow range of age and monthly income levels.

**Table 1: Personal characteristics of respondents**

| **Age of respondents (years)** | **f** | **%** |
|---|---|---|
| 18-19 | 20 | 40 |
| 20-21 | 30 | 60 |
| Total | 50 | 100 |
| **Household income of respondents (PKR)** | **f** | **%** |
| 15,000-17,000 | 9 | 18 |
| 18,000-20,000 | 17 | 34 |
| 21,000-23,000 | 5 | 10 |
| 24,000-26,000 | 19 | 38 |
| Total | 50 | 100 |
| **Mode of transport to/from university** | **f** | **%** |
| Public transport | 18 | 36 |
| University bus | 14 | 28 |
| Motorcycle | 10 | 20 |
| Foot | 5 | 10 |
| Total | 50 | 100 |
| **Prior knowledge of cancer through electronic media** | **f** | **%** |
| Yes | 0 | 0 |
| No | 50 | 100 |
| **Prior knowledge of cancer through print media or textbooks** | **f** | **%** |
| Yes | 0 | 0 |
| No | 50 | 100 |

***Source***: Author's calculations.

The results do not yield any significant differences across income levels. The results of a t-test analysis to determine the pre- and post-exposure readings of respondents belonging to two broad income brackets included in the sample are given in Table 2.

**Table 2: Difference in pre- and post-exposure health knowledge and behaviors of respondents from two income brackets**

| | Income bracket | Mean | SD | df | t | p |
|---|---|---|---|---|---|---|
| Pre-exposure knowledge | 15,000-19,500 | 10.82 | 2.675 | 48 | 0.007 | 0.994 |
| | 19,501-25,000 | 10.82 | 2.378 | | | |
| Post-exposure knowledge | 15,000-19,500 | 12.24 | 2.513 | 48 | -0.485 | 0.630 |
| | 19,501-25,000 | 12.61 | 2.585 | | | |
| Pre-exposure behavior | 15,000-20,000 | 3.94 | 1.478 | 48 | 0.416 | 0.679 |
| | 20,000-25,000 | 3.76 | 1.480 | | | |
| Post-exposure behavior | 15,000-20,000 | 5.12 | 1.933 | 48 | -0.057 | 0.955 |
| | 20,000-25,000 | 5.09 | 1.355 | | | |

***Source***: Author's calculations.

A comparative description of participants' pre- and post-exposure responses to the health knowledge questions pertaining to breast cancer is given in Table 3.

**Table 3: Pre- and post-exposure health knowledge of participants**

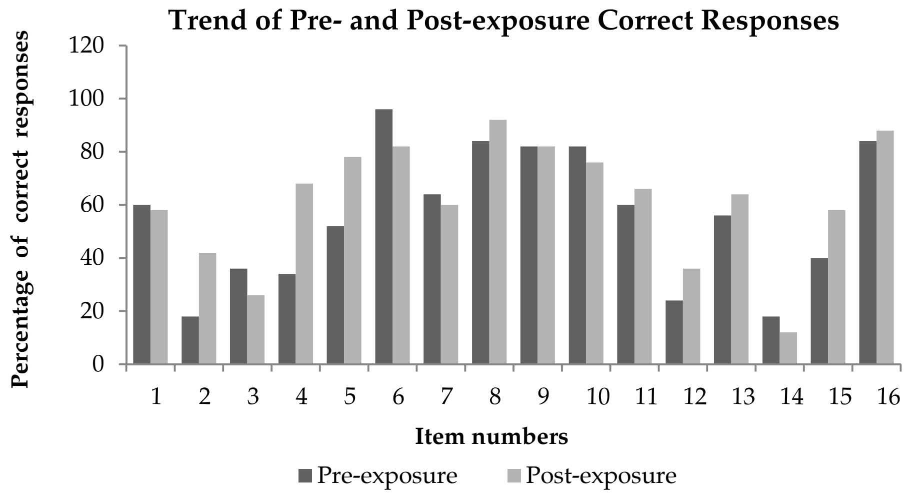
| | | Yes | | No | | Total | |
|---|---|---|---|---|---|---|---|
| **No.** | **Questions** | **f** | **%** | **f** | **%** | **f** | **%** |
| 1. | Is breast cancer always a fatal disease? | 30 | 60 | 20 | 40 | 50 | 100 |
| | | **29** | **58** | **21** | **42** | | |
| 2. | Can an ordinary looking change in your breasts be an indication of cancer? | 9 | 18 | 41 | 82 | 50 | 100 |
| | | **21** | **42** | **29** | **58** | | |
| 3. | Is breast cancer directly related to any type of food intake? | 18 | 36 | 32 | 64 | 50 | 100 |
| | | **13** | **26** | **37** | **74** | | |
| 4. | Do you think it has any relationship with the cessation of menstruation? | 17 | 34 | 33 | 66 | 50 | 100 |
| | | **34** | **68** | **16** | **32** | | |
| 5. | Is heredity related to the development of the breast cancer? | 26 | 52 | 24 | 48 | 50 | 100 |
| | | **39** | **78** | **11** | **22** | | |
| 6. | Are women who smoke at higher risk of developing breast cancer? | 48 | 96 | 2 | 4 | 50 | 100 |
| | | **41** | **82** | **9** | **18** | | |
| 7. | Is there any relationship between the development of breast cancer and breastfeeding? | 32 | 64 | 18 | 36 | 50 | 100 |
| | | **30** | **60** | **20** | **40** | | |

| | | Yes | | No | | Total | |
|---|---|---|---|---|---|---|---|
| **No.** | **Questions** | **f** | **%** | **f** | **%** | **f** | **%** |
| 8. | Does breast cancer necessarily affect a woman's marital life negatively? | 8 | 16 | 42 | 84 | 50 | 100 |
| | | **4** | **8** | **46** | **92** | | |
| 9. | Does breast surgery for the treatment of cancer, always put an end to a woman's beauty? | 41 | 82 | 9 | 18 | 50 | 100 |
| | | **41** | **82** | **9** | **18** | | |
| 10. | Does breast cancer always restrict a woman's social role? | 41 | 82 | 9 | 18 | 50 | 100 |
| | | **38** | **76** | **12** | **24** | | |
| 11. | Can a female's breast be reconstructed? | 30 | 60 | 20 | 40 | 50 | 100 |
| | | **33** | **66** | **17** | **34** | | |
| 12. | If yes, can it make a woman as normal as before? | 12 | 24 | 38 | 76 | 50 | 100 |
| | | **18** | **36** | **32** | **64** | | |
| 13. | Are woman who suffer from breast cancer able to conceive? | 28 | 56 | 22 | 44 | 50 | 100 |
| | | **32** | **64** | **8** | **16** | | |
| 14. | Do you think breast cancer is infectious and can spread from one woman to another? | 9 | 18 | 41 | 82 | 50 | 100 |
| | | **6** | **12** | **44** | **88** | | |
| 15. | Can prolonged stress cause breast cancer? | 20 | 40 | 30 | 60 | 50 | 100 |
| | | **29** | **58** | **21** | **42** | | |
| 16. | Do you think breast cancer is curable? | 42 | 84 | 8 | 16 | 50 | 100 |
| | | **44** | **88** | **6** | **12** | | |

Note: Post-exposure readings are given in bold and prominent improvements highlighted.
***Source***: Author's calculations.

The greatest improvement in knowledge is observed for question 5 ("Is heredity related to the development of the breast cancer?")—from 52 to 78 percent. This is followed by question 2 ("Can an ordinary looking change in your breasts be an indication of cancer?"), where the percentage of respondents giving the correct answer rose from 18 to 42 percent. Questions 15 and 12 also show an improvement, from 40 to 58 percent, and from 24 to 36 percent, respectively. Figure 1 illustrates the trends in correct responses in the pre- and post-exposure phases. Clear-cut improvements occur in all cases except four.

**Figure 1: Correct responses in the pre- and post-exposure phase**




Participants' pre- and post-exposure descriptions of various aspects of the diagnosis and treatment of breast cancer are given in Table 4.

**Table 4: Description of breast cancer-related concepts**

| | Pre-exposure (plain) and Post-exposure (bold) | |
|---|---|---|
| **Responses** | **F** | **%** |
| Accurate description of BSE | 43 | 86 |
| | **42** | **84** |
| Accurate description of mammogram | 21 | 42 |
| | **29** | **58** |
| Accurate understanding of the population at risk | 39 | 78 |
| | **37** | **74** |
| Accurate description of mastectomy | 28 | 56 |
| | **36** | **72** |
| Accurate description of biopsy | 26 | 52 |
| | **25** | **50** |

Note: Post-exposure readings are given in bold and prominent improvements highlighted.
***Source***: Author's calculations.

Breast cancer-related health knowledge means obtained on both occasions were compared employing the t-test (Table 5).

**Table 5: Difference between pre- and post-exposure health knowledge of participants**

| Pre-exposure health knowledge | | Post-exposure health knowledge | | | | |
|---|---|---|---|---|---|---|
| **M** | **SD** | **M** | **SD** | **df** | **T** | **p** |
| 10.82 | 2.455 | 12.48 | 2.541 | 49 | -3.877 | 0.000 |

***Source***: Author's calculations.

The two means, pre- and post-exposure, are found to be significantly different: t (49) = 3.877, p = 0.000. This lends strong support to the hypothesis that, if women are provided health-related information, their scores for the health knowledge measure will increase.

The pre- and post-exposure reports on participants' health behavior reveal a number of significant findings (Table 6). Their pre-exposure health behavior indicates a number of areas that need attention. Pre-exposure, most participants had neither read any health-related information on breast cancer in the form of newspapers, books, or health education material, nor had they watched any television programs on the subject. Moreover, 82 percent said that they did not practice any type of BSE. Of the remaining 8 percent, only 3 percent reported having done so occasionally.

The post-exposure reports on breast cancer-related health behavior also yielded significant improvements: all the respondents (100 percent) said that health education activities should be carried out in educational institutions to disseminate information on breast cancer (question 6); 86 percent showed an interest in conducting research on breast cancer (question 8). Twenty-eight percent of the respondents reported that they occasionally performed BSE. There was an increase in respondents' interest in all aspects of breast cancer-related health behavior. The most significant change occurred in their response to question 3. In the pre-exposure phase, only 18 percent of the participants reported having practiced BSE; this percentage rose to 52 in the post-exposure phase (Table 6).

**Table 6: Pre- and post-exposure health behavior of participants**

| No. | Health behavior indicators | Yes | | No | | Total | |
|---|---|---|---|---|---|---|---|
| | | f | % | f | % | f | % |
| 1. | Do you read any health-related segments or articles about breast cancer in the newspaper? | 21<br>**28** | 42<br>**56** | 29<br>**22** | 58<br>**44** | 50 | 100 |
| 2. | Have you ever read any books or pamphlets, or watched any TV programs related to breast cancer? | 24<br>**36** | 48<br>**72** | 26<br>**14** | 52<br>**28** | 50 | 100 |
| 3. | Do you practice any type of examination of your breasts? | 9<br>**26** | 18<br>**52** | 41<br>**24** | 82<br>**48** | 50 | 100 |
| 4. | ** (See end of table) | | | | | | |
| 5. | If you were to go to your family doctor, would you like to talk to him or her about any change/growth in your breasts?** | 23<br>**29** | 46<br>**58** | 27<br>**21** | 54<br>**42** | 50 | 100 |
| 6. | Do you think there should be some kind of lectures, campaigns, and seminars in colleges or universities to impart information about breast cancer? | 45<br>**50** | 90<br>**100** | 5<br>**0** | 10<br>**0** | 50 | 100 |
| 7. | Would like to join a breast cancer-related diagnosis/treatment campaign? | 30<br>**39** | 60<br>**78** | 20<br>**11** | 40<br>**22** | 50 | 100 |
| 8. | Would you like to do research on breast cancer? | 41<br>**43** | 82<br>**86** | 9<br>**7** | 18<br>**14** | 50 | 100 |

** Question 4 (If yes, when?)

| Yearly | | Occasionally | | Never | | No response | | Total | |
|---|---|---|---|---|---|---|---|---|---|
| f | % | f | % | f | % | f | % | f | % |
| 0 | 0 | 3 | 6 | 3 | 6 | 44 | 88 | 50 | 100 |
| **4** | **8** | **14** | **28** | **3** | **6** | **29** | **58** | 50 | 100 |

Note: Post-exposure readings are given in bold and prominent improvements highlighted.
***Source***: Author's calculations.

The mean scores for health behavior were also compared to determine whether the provision of health information and knowledge had made a difference (Table 7). The t-test analysis yields t (49) = 4.595, p = 0.000, indicating a significant difference. Participants' post-exposure responses generate a mean value higher than that obtained in the pre-exposure phase. This finding supports our second hypothesis, i.e., that if women are provided health-related information, their scores for the health behavior measure will increase.

Participants also gave a separate report on the health behavior changes that took place after their exposure to health education. As Table 8 shows, 100 percent of the respondents found the exercise to be informative, and 90 percent felt they would like to receive more such information on other diseases. Another 90 percent thought that early detection could help prevent the serious nature of most diseases, while 92 percent also believed that the risk factors associated with breast cancer could be minimized by acquiring the relevant information. A significant improvement in health protective behavior was reported by 60 percent of the participants, who said that they had carried out BSE after receiving information about it.

**Table 7: Difference between pre- and post-exposure health behaviors**

| Pre-exposure health behavior | | Post-exposure health behavior | | | | |
|---|---|---|---|---|---|---|
| **M** | **SD** | **M** | **SD** | **df** | **t** | **p** |
| 3.82 | 1.466 | 5.10 | 1.555 | 49 | -4.595 | 0.000 |

***Source***: Author's calculations.

**Table 8: Post-exposure report on behavioral change**

| | | Yes | | No | |
|---|---|---|---|---|---|
| | **Health behavior indicators** | **f** | **%** | **f** | **%** |
| 1. | Would you like to read informative literature, or watch informative video CDs related to other diseases? | 45 | 90 | 5 | 10 |
| 2. | Have you found it informative to read a pamphlet and watch a CD about breast cancer? | 50 | 100 | 0 | 0 |
| 3. | Have you examined your breasts after obtaining information about it? | 30 | 60 | 20 | 40 |
| 4. | Have you talked about breast cancer with other individuals? | 38 | 76 | 12 | 24 |
| 5. | Would you like to obtain further information related to breast cancer? | 43 | 86 | 7 | 14 |
| 6. | Can information about breast cancer help you prevent risk factors related to its development? | 46 | 92 | 4 | 8 |
| 7. | Has this information produced any change in your health-related beliefs? | 38 | 76 | 12 | 24 |
| 8. | Do you think that most diseases can be prevented if their onset is detected in time? | 45 | 90 | 5 | 10 |

***Source***: Author's calculations.

As the table shows, 76 percent of the participants had transferred the information acquired during the study to others. Of these, 42 percent had talked to friends and 12 percent to family members. Another 12 percent had kept the information to themselves.

A statistical analysis of this data involves identifying the correlation between the variables being investigated. Table 9 presents the correlation coefficient for health knowledge and health behavior at two levels, i.e., between pre-exposure health knowledge and behavior, and between post-exposure health knowledge and behavior. The correlation between pre-exposure health knowledge and behavior is not significant, but does indicate a positive relationship. The correlation between post-exposure health knowledge and behavior is found to be significant: $r(50) = 0.339$, $p < 0.05$.

**Table 9: Correlations between health knowledge and health behavior**

| | | |
|---|---|---|
| Pre-exposure knowledge and pre-exposure behavior | Pearson correlation | 0.246 |
| | Sig. (2-tailed) | 0.085 |
| | N | 50 |
| Post-exposure knowledge and post-exposure behavior | Pearson correlation | 0.339 |
| | Sig. (2-tailed) | 0.016 |
| | N | 50 |
| | Sig. (2-tailed) | |

***Source***: Author's calculations.

## 4. Discussion

This study was designed to examine the impact of health information/knowledge provision on health-related beliefs and behaviors. Our main assumption was that women's health status can be improved if they adopt health protective and health enhancing behaviors, and that people can be expected to do so only when they are aware of (i) the existence of such behaviors, and (ii) the possibility that they are in control of their own lives and capable of practicing these behaviors.

People cannot be expected to adopt healthy lifestyles unless they are aware that such practices exist and understand their importance. Even people who are highly educated in the conventional sense might adopt unhealthy practices if they have learnt that such behaviors are beneficial for their health—hence the significance of appropriate health-related knowledge. We hypothesized that women's health-related knowledge and behaviors could be enhanced by providing the relevant information.

These hypotheses were formed on the basis of the available literature on the subject. Many studies conducted using a range of samples across cultures have found that health knowledge provision improves related health practices. In cultures such as ours, where the poor health status of women is a matter of concern for health authorities, the provision of helpful information could enable women to look after their health better, and lower the burden of high medical expenditure on the national exchequer.

We chose to examine breast cancer and its corresponding health knowledge and behavior because it is a disease that poses a serious threat to women's health, but one that can have a very good prognosis if detected at an early stage. Research evidence shows that most women report for medical consultation at a late stage of the disease. If women were better aware of the nature, risk factors, symptoms, and treatment options involved, they could be expected to adopt health protective behaviors.

A number of significant improvements were recorded in the sample participants' breast cancer-related knowledge and behaviors. Between the two phases, we found that a larger number had read health-related segments in newspapers, books, or health education materials, and watched television programs on the subject. The number who had performed BSE had almost tripled. Most post-exposure changes were found to be statistically significant. However, the most significant findings were those yielded by the t-tests carried out to examine the significance of the difference between the pre- and post-exposure means of breast cancer-related knowledge and behaviors. The improvement in both knowledge and behavior was noted and found to be statistically highly significant.

All the changes or improvements in participants' responses indicated a positive shift in their health knowledge and behavior. This underscores the realization that, if a small-scale session on health information provision could have such a significant impact, then it should be possible to bring about a change at a larger level by involving other agents of social change. The mass media and textbook developers could play an important role in this regard.

The large majority of participants said that they would like to gain more knowledge about breast cancer and similar information about other health issues. All of them found the exercise to be informative, and most felt that information about breast cancer could help prevent risk factors, while early detection could help prevent most diseases. Most participants said they had practiced BSE after having learnt about the procedure.

These reports of behavioral change indicate that women are basically willing to acquire knowledge about issues pertaining to their health. We saw that the knowledge they had about health issues, including reproductive health, was not based on expert opinions because most of them had never read anything on the subject, discussed such issues with anyone, or watched health-related programs on television. Therefore, when this study provided them with an opportunity to acquire the relevant information, they expressed an interest in gaining more information on such subjects.

The value of this exercise acquires even more significance when we consider that our sample comprised educated females studying at a well-reputed women's university in the provincial capital. If this segment of the female population has insufficient, incomplete, or inaccurate knowledge of health issues, then we can expect women from less privileged regions to be even less knowledgeable.

Our findings have serious implications. In cases of breast cancer, it is usually the patient who first detects a lump and then seeks medical advice. The earlier the detection, the better her prognosis might be. Still, many women tend to ignore such changes in their bodies for some time and only seek medical help once they have reached the second or third stage of the disease's development. This is often because they were not aware that an ordinary looking change or growth could have serious, life threatening consequences. There are also women who are aware that changes in their body should not be ignored, but who delay seeking medical attention because they do not know how to detect the change at an early stage. These women do not perform BSE through lack of awareness of the procedure, carelessness, or procrastination.

In these and similar situations, accurate knowledge and awareness are two highly significant variables. Women need to possess health knowledge before they can adopt healthy lifestyles and health protective behaviors. In contemporary Pakistani society, little attention is paid to health education. Neither school textbooks nor curricula teach personal health, especially reproductive health. The mass media does not play an active role in the provision of public health education. The participants in this study were educated females who had been exposed to a variety of academic stimulants in the last 13 or 14 years of formal education, but most of them lacked the essential knowledge that could be vital to a woman's health. It is, therefore, imperative that policymakers and other stakeholders join hands to find ways of promoting health and enhancing wellbeing through health education.

## 5. Conclusion

This study has shown that health information provision or health education can bring about significant positive changes in health related-behaviors. We have seen that formal education does not contribute as much to health knowledge, behaviors, or beliefs such as self-efficacy. Exposure to health-related information and subsequently enhanced awareness not only improves health knowledge but also encourages healthy practices.

Health education campaigns pertaining to breast cancer and other aspects of reproductive health should be designed and run through radio and television programs. Formal education should incorporate health education as part of the curricula at all academic levels. Simple messages pertaining to issues such as personal hygiene could be introduced at the school level, while awareness of health-promoting behavior, disease prevention, and the identification of symptoms of common diseases could be raised at college or university level. The print media should also be involved in delivering health protective messages.

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