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Evaluation of Energy Cleanability Gap and its Impact on Sustainable Economic Development

ABSTRACT

The transition from traditional to sustainable energy is nothing without easy access to clean energy. Therefore, different economies have made smooth transitions, but still, there is a gap in energy cleanability. Here, this study adopted two stage-analyses; initially, it presents an overlook of energy cleanability transition by applying Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) with entropy weightage in low-middle & upper middle-income countries. The fallout of TOPSIS discloses the outcomes and finds more divergence trends in lower-middle-income countries. Furthermore, the current study examined the impact of the energy cleanability gap on economic development in selected panels from 2000 to 2019. Then, unclean energy is to blame for the declining trend in economic development. Furthermore, sustainability in the energy transition is more required as it has its costs and benefits and needs more government commitment and regulatory changes. So, avoiding such vulnerabilities requires massive financing to tackle them and improve flexibility in economic development.

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Author's contribution in the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

United Nations General Assembly adopted a resolution in 2015 to make definite access to reliable, affordable, and clean energy for each individual (SDG-7) by 2030. The choices of energy for the kitchen and other purposes are essential to attain SDG-3 (good health and welfare). Furthermore, the literature proves that burning solid fuels releases carbon monoxide and other harmful particulate matter. Primarily, high health concerns are associated with all human beings. Given the above facts, SDG-7 aims to guarantee the achievement of the maximum SDG-2030 objectives.

High-income economies have made significant progress toward their SDG-7 goals in the last few years. Furthermore, these transition progress are connected with an efficient public policy to enhance widespread access to environment-friendly fuels. This transition is relatively low in upper-middle-income economies (UMIE), where 30-35% of households use unclean fuels for cooking. However, such a paradigm shift in low-middle income economies (LMIE) is long behind; primarily, contaminated fuels are still used in rural areas on a large scale. In particular, 70% of rural households rely on unclean energy for cooking due to poor quality of life, income inequality, and other social issues. One of the barriers preventing homes from effectively switching to clean energy could be the frequent unavailability or load shedding in the LMIE. Therefore, many socioeconomic issues originate from unclean fuels and still spreading in LMIE.

Numerous projects are under completion among different regions, and countries anywhere access to clean energy infrastructure is inadequate. Many earlier development projects require better access to low-cost and sustainable energy. An extraordinary transition to energy cleanability is underway in upper and lower-income countries (LMIE & UMIE). Making this transition easy can guide further rapid moves forward in community welfare than would or else be viable. Therefore, a rapid novelty in infrastructure, technology, market, organization, and strategies make energy cleanability transitions more feasible than before (Akhtar, M. J., Ashraf, W., & Rehman, H., 2020).

As well as meeting growing energy demands and extenuating greenhouse gas discharge, transitions to energy cleanability can help households who experience energy and economic poverty. For case, low-cost and clean energy can frankly perk up the income of low-income households by increasing their income status, enhancing productivity in the agricultural sector, and saving precious time. Clean energy also contains other benefits, educational achievement, better literacy, more free time, and improved access to information and news via radio, mobile phone, and television. Moreover, energy cleanability sources can perk up welfare and diminish hard work simultaneously as they expand work and free time. At the same time, empirical studies highlight frequent reimbursement of energy cleanability transition. Understanding the drivers of such changes and their effects on human welfare is critical for the continuing and potential energy cleanability transitions to be successful across countries and regions.

The triennial report of The Committee of Development Plans, Council (2022) revealed that LMIEs are highly vulnerable and face shocks of environmental changes due to their poor socioeconomic condition. Further, these ecological changes slow their pace toward sustainable development and structural reforms. Moreover, as developed countries across the globe set their paths towards attaining significant progress of the SDGs-2030, the LMIE is facing massive poverty and unemployment. Furthermore, these economies face the threat of low illiteracy levels, low life expectancy, and more income inequality. In this view, the UNDP and the University of Oxford (2021) report that these factors drive the LMIE economies un-deliberately towards plain growth instead of sustainable planning.

This paper aims to compare the sustainable energy transition gap in the context of SDGs-2030 in selected countries and estimate the impact of the energy cleanability gap on sustainable economic development for the period 2000-19. The critical research problems with the perspective of SDGs-2030 are:

- What is the current energy cleanability situation in selected countries?
- How does energy cleanability impact economic development?
- How does development expenditure determine economic development?
- How does industrial value addition determine economic development?
- How does trade liberalization determine economic development?

This study has two parts, and the first use the TOPSIS technique to compare where various countries are in their energy cleanability transition. In the 2nd step, a regression process is used to explore the connection between economic development and energy cleanability transition. This study used various predictors of economic development to analyze the impact. The outcomes can assist in making economic development policy to achieve SDGs-2030 with an energy cleanability transition.

2. LITERATURE REVIEW

The literature lacks a unified definition of the energy transition gap (Akhtar, M. J., Rehman, H., & Abbas, Q. (2022). Clean cooking describes the way that does not produce indoor air pollution (such as carbon monoxide or particulate matter) or, if these gases are created, the quantity of these gases is very deficient (Akhtar, M. J., Ashraf, W., & Rehman, H., 2020). Socioeconomic considerations, energy preferences, technological advancements, the availability of energy sources, and energy cost are all critical influencing factors. In addition, the community's preferences, gender standards, recognized traditions, and economic structure are entwined with using unclean fuels for cooking. Economic development, along with the promotion of sustainability, is currently an increasing concern on a worldwide scale. Sustainability requires cooperation, accuracy, responsibility, and teamwork in the economic development plan (Akhtar, M. J., Rehman, H., & Abbas, Q. (2022).

Furthermore, numerous assessments have been produced (Yao et al., 2020; Munten et al., 2021; OECD, 2019; Li et al., 2022; (Akhtar, M. J., Ashraf, W., & Rehman, H., 2020); (Akhtar, M. J., Rehman, H., & Abbas, Q. (2022)):, and others have looked into the relationship between overall economic development, energy consumption, and other critical economic vectors. The study by (Yao et al., 2020) conducted a systematic review and concluded that the same principles do not bind studies to the connection between economic development and energy sources. Their study concluded that numerous scholars had investigated the empirical impact of total energy consumption on economic growth. Moreover, the study of Munten et al. (2021) captured the direct effects of energy concerns on development. It concluded that the spillover effect between total energy consumption & economic growth on human health. Therefore, he further added in his policy implications that clean fuel is a basic need to enhance livelihoods and, more broadly, human development. Now, it is a rising subject of SDGs-2030.

Furthermore, the study of Manole et al. (2017); Li et al. (2022) focused on measures to combat energy-related impacts on health and observed that energy consumption mostly depends on fossil inputs, even in developed countries, which negatively affects health. Furthermore, the study by OECD (2019) observed that unclean energy would continue to dominate the energy mix in the future and remain an essential energy source for 10 to 15 years in LMIE economies worldwide.

The study by Garba and Bellingham (2021) found four potential relationships in the literature (neutral, conservation, growth, and spillover theories). Furthermore, they define the unbiased approach when there is an insignificant relationship between energy and economic development. Moreover, conservation theory focusing on demand management and reducing the use of fossil fuels, among others, would not negatively affect the nation's economy. Thirdly, according to the growth hypothesis, energy is necessary for the nation's economic development. Finally, the spillover theory applies when there is a two-way causal relationship between energy and economic growth.

Regarding low-middle income economies (LMIE), the study by Akhtar, M. J., Rehman, H., & Abbas, Q. (2022) found that the problems with energy are well known, and researchers are increasingly looking at how energy influences the region's growth. More recently, using the Fully Modified Ordinary Least Square (FMOLS) as well as Dynamic Ordinary Least Square (DOLS) method, (Li et al., 2022) studied the relationship between energy use and economic growth in LMIE. Applying the same strategy, (Akhtar, M. J., Ashraf, W., & Rehman, H., 2020) analyzed how energy and economic development. The study by (Li et al., 2022) that looks into the energy-growth nexus for LMIE and the relationship between energy and economic growth are among recent works attempting to understand this relationship. However, the study by (Akhtar, M. J., Rehman, H., & Abbas, Q. (2022) and several other studies investigating these linkages have observed varying conclusions.

This paper crammed a gap in the literature by investigating the energy cleanability gap assessment and its empirical impact on economic development in all income panels segregated by WDI using FMOLS and DOLS techniques. Further, including R&D expenditure, industrial value addition, and trade liberalization in the analysis made this study more comprehensive.

In various aspects, this work makes a sufficient and significant contribution to the growing body of knowledge on the relationship between the use of unclean energy and the success of sustainable development. This research tries to fill in some of the knowledge gaps currently in the study linking impure energy and development outcomes. Initially, this article examines the connections between energy usage from unclean sources as a critical threat to growth from a supply-side perspective, given the relationship between energy produced from filthy energy sources and development, as mentioned in this section. Analysis in earlier studies has concentrated chiefly on demand or overall energy consumption. The modeling paradigm lacks a supply-side analysis considering institutional, economic, and demographic influences on developmental quality.

The use of a broad assessment in this study rather than just one indicator, the energy cleanability gap (ECG) index, is its second contribution to existing knowledge. The ECG records the deterioration of human health, the insecurity of food and water sources, and the existence of toxic compounds that impact the environment. The results based on the ECG offer greater analytical integrity with more substantial policy implications. The ECG hasn't been considered in previous studies' modeling frameworks.

The fact that previous empirical studies did not assess how clean energy influences the world's collective participation in preventing global economic development is a third significant contribution to the new corpus of knowledge. The United States of America's decision to leave the Paris Climate Change Agreement exemplifies the lack of international commitment. Interestingly, there is little empirical research on how committed the global community is to addressing weaknesses in economic growth.

The study's final new insight is that the energy cleanability gap is the primary factor that can result in health problems. Nonetheless, the topic of discussions about international economic development and the energy cleanability gap is infrequent with this in-depth. This research broadens the conversation about how dirty energy affects economic growth and emphasizes that effect. It also provides empirical support for that claim. It attempts to increase awareness and attract more attention to energy-producing nations using unclean energy produced by efficient energy policies to further economic development. It is anticipated that governments of these countries with unclean energy will successfully create their economic development plans to realize their goals for a more healthy and robust global economy.

3. DATA AND METHODOLOGY

This research article contains two different phases. The 1st phase was committed to evaluating the energy cleanability assessment in selected countries for the period 2000–2019 by using TOPSIS (Che et al., 2021). Therefore, we choose the TOPSIS model to incarcerate the performance and dynamics while concurrently evaluating the stability within and across the dimension. In 2nd phase, this study examined the empirical connection among selected variables using panel-FMOLS. Moreover, the study used DOLS for robustness (Li et al., 2022) regression models.

3.1 Data

We focus on the analysis of 73 countries (see Table 1) from 2000 to 2019. Energy cleanability was obtained using the TOPSIS index form using the following variables mentioned in Table 2, and comparative assessments were made among selected countries. Energy cleanability data are obtained from the 2021 WDI and IEA. Finally, the data source of total development expenditure, industrial value addition, and trade liberalization are taken in WDI-2021.

3.2 TOPSIS Analysis

This study employed the TOPSIS methodology. TOPSIS is a mathematical modeling technique introduced by Ching Lai Hwang and Yoon in 1981, with further developments by Yoon in 1987 and Hwang, Lai, and Liu in 1993 wikipedia.org (2019) to evaluate the relative closeness to the ideal situation. In the current analysis, this study engaged TOPSIS to assess the dynamics of energy cleanability during the period 2000–2019. TOPSIS consent exchanges between criteria, where superior outcomes in another standard can cancel a bad result in one measure. This process provides a more natural form of modeling than non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs.

Z is processed to get the standard evaluation matrix.

$$Z = [\beta_{ij}] \tag{1}$$

Where β_{ij} represent the attainment of vectors j for economies. $i, i \in [1, m], j \in [1, 8]$, M is the procedure to acquire the typical decision-based matrix.

$$M = [\gamma_{ij}]_{m\times 8} \tag{2}$$

While the significance of vectors in energy cleanability assessment changes, the weight through entropy is espoused in this study. Agree to $K = [k]_{ij}$ be the standard weighted matrix.

$$k_{ij} = \sum_{i=1}^{m} \gamma_{ij} \times \omega_j, \omega_j > 0 \; and \sum \omega_j = 1 \tag{3}$$

Further, the random assortment towards ideal solutions makes a rank reversal process. The restrictions of each vector right through are defined as complete optimistic and pessimistic idyllic solutions. Due to data availability limitations, the selected panel contains only 129 countries in this study. So, absolute ideal solutions can be written as follows:

$$K^{+} = \{k^{+}_{1worst}, k^{+}_{2worst}, \cdots, k^{+}_{8worst}\} \tag{4}$$

Where k^{+}_{jworst} is the least amount of indicator j.

Table 1: Selected Countries codes and Variables

Code	Countries	Code	Countries	Code	Countries	Code	Countries
ALB	Albania	GTM	Guatemala	VEN	Venezuela, RB	MNG	Mongolia
ARG	Argentina	IRN	Iran, Islamic Rep.	DZA	Algeria	MAR	Morocco
ARM	Armenia	IRQ	Iraq	AGO	Angola	NPL	Nepal
AZE	Azerbaijan	JAM	Jamaica	BGD	Bangladesh	NIC	Nicaragua
BLR	Belarus	JOR	Jordan	BEN	Benin	NGA	Nigeria
BIH	Bosnia and Herzegovina	KAZ	Kazakhstan	BOL	Bolivia	PAK	Pakistan
BWA	Botswana	LBN	Lebanon	KHM	Cambodia	PHL	Philippines
BRA	Brazil	MYS	Malaysia	CMR	Cameroon	SEN	Senegal
BGR	Bulgaria	MEX	Mexico	COG	Congo, Rep.	LKA	Sri Lanka
CHN	China	NAM	Namibia	CIV	Cote d'Ivoire	TZA	Tanzania
COL	Colombia	MKD	North Macedonia	EGY	Egypt, Arab Rep.	TUN	Tunisia
COD	Congo, Dem. Rep.	PRY	Paraguay	SLV	El Salvador	UKR	Ukraine
CRI	Costa Rica	PER	Peru	GHA	Ghana	UZB	Uzbekistan
CUB	Cuba	RUS	Russian Federation	HND	Honduras	VNM	Vietnam
DOM	Dominican Republic	SRB	Serbia	IND	India	ZMB	Zambia
ECU	Ecuador	ZAF	South Africa	IDN	Indonesia	ZWE	Zimbabwe
EST	Estonia	THA	Thailand	KEN	Kenya		
GAB	Gabon	TUR	Turkey	KGZ	Kyrgyz Republic		
GEO	Georgia	TKM	Turkmenistan	MDA	Moldova		

Table 2

Name	Variables	Description	References	Data Source
Clean Energy	Access clean cooking energy	(% population)	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022; Che et al., 2021)	WDI
	Renewable energy	(% population)	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022)	IEA
ED	Economic development index	Index (0 to 1)	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022)	UNDP
IND	Industrial value addition	[Industry (including construction) value Added % of GDP]	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022)	WDI
TRD	Trade liberalization	[Trade % of GDP]	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022)	WDI
R&D	Total development expenditure	[Education and Health expense % of GDP]	(Akhtar, M. J., Rehman, H., & Abbas, Q., 2022)	WDI
CL	Energy Cleanability Gap	Index (0 to 1)	(Che et al., 2021)	WDI, IEA, BP

Absolute negative ideal solutions are written as:

$$K^- = \{k^-_{1best}, k^-_{2best}, \cdots, k^-_{8best}\} \tag{5}$$

Where k^-_{jbest} is maximum of indicator j, virtual negative ideal solutions are introduced to pick up a better ideal condition.

$$K^* = \{k^*_1, k^*_2, \cdots, k^*_8\}\ (where k^*_j = 2k^-_{jworst} - k^+_{jbes}) \tag{6}$$

Alteration through the Absolute negative ideal solutions K^- and to keep away from Euclidean distance withdrawal.

$$S^+_i = \sqrt{\sum_j^8 \left(k_{ij} - K^+_{jbes}\right)^2} \tag{7}$$

$$S^-_i = \sqrt{\sum_j^8 \left(d_{ij} - K^*_j\right)^2} \tag{8}$$

The proximity is apparent as:

$$E^*_i = \frac{S^+_i}{S^+_i + S^-_i} \tag{9}$$

Where $0 \leq E^*_i \leq 0.1$ the countries with E^*_i, in order of least to most significant decrease, are organized and the countries with occurrence lower unclean energy.

3.3 Methodology

This study considers the following regression model:

$$ED_{it} = \alpha_{it} + \delta_1 lnCL_{it} + \delta_2 CL^2_{it} + \delta_3 lnEXP_{it} + \delta_4 lnTRD_{it} + \delta_5 lnIND_{it} + \varepsilon_{it} \tag{10}$$

Where; $t = 1,2, \dots, T,\ i = 1,2, \dots, N,\ t,$ represents time across the period, T; i symbolized here cross-section in the selected panel, α_{it} are intercept and ε_{it} indicate anticipated residual, which reveals the divergence from the long-term association.

In equation (01), if the EKC hypothesis holds, the coefficient of energy cleanability must be statistically significant. Different studies argued that cointegration methods help classify the variables' links in literature. Various techniques are adopted to check data set validation, and unit root tests are one of the more critical techniques for the stationarity characteristics of the selected variables.

3.5 Unit Root Test

The unit root test is necessary for determining the cointegration test procedures. It presumptively predicts that the variable will move toward a long-run equilibrium in its respective period. Because of the prolonged timeframe and inconsistent issues that the panel data in this study confronts, spurious regression is likely to be carried out. In this way, the variables in the model must be stationary for the panel regression process. Thus, the Augmented Dickey-Fuller (henceforth ADF) test gave rise to the Levin et al. (2002) (LLC) method, which is the most often used in the panel methodology for unit root tests. LLC asserted that all groups have the same autoregressive parameters under null and alternative assumptions. Hence, to the description for the leeway of correlation and possible spillage crossways countries, the structure of the LLC analysis may be specified as follows:

$$\Delta Y_{it} = \rho Y_{it} + \alpha_{0i} + \alpha_{1i} t + u_{it},\ i = 1,2, \dots, N,\ t = 1,2, \dots, T \tag{11}$$

Where, t includes both the individual special effects (α_i) and the time tendency. To follow a stationary ARMA approach for each individual, u_{it} it is intended to be distributed but independently for every individual.

$$u_{it} = \sum_{j=1}^{\infty} \theta_{ij}\, u_{it-j} + \epsilon_{it} \tag{12}$$

The IPS method is the expansion of LLC however permits heterogeneity by allowing for the employ of means of the ADF analysis and probability chance. Consequently, unlike LLC, short panels are required for a higher test power (Behera et al., 2020). The IPS panel stationarity regression is expressed as follows for observation group N and period T:

$$\Delta X_{it} = \alpha_i + \pi_{it} + \beta_i X_{i,t-1} + \sum_{j=1}^{k} \varphi_{it}\, \Delta X_{i,t-1} + \epsilon_{it} \tag{13}$$

Conversely, both (LLC&IPS) procedures have the shortcoming of pretentious independence crosswise segregation of the selected panel (Garba&Bellingham, 2021). It supposes a homogeneous group.Im et al. (2003) developed the IPS unit root test. Using augmented Dickey-Fuller (ADF) regression, the method obtains the t-statistics value after adjusting for heterogeneity.

3.6 Cointegration Techniques

Furthermore, this study performs cointegration techniques, i.e., Pedroni (2004) and Kao (1999) tests that manage the issue and reliable results. The Pedroni techniques tackle homogeneity and heterogeneity as well. Mathematically it is represented as:

$$ED_{it} = \alpha_i + \lambda_{it} + \sum_{j=1}^{m} \beta_{j,i} CL_{j,it} + \zeta_{it} \tag{15}$$

In this equation; ζ_{it}, are residuals and Kao test based on homogeneity assumption across all panels. They follow a similar draw as Pedroni but are based on the premise of homogeneity across boards with:

$$CL_{it} = \alpha_i * ED_{it}\beta + \omega_{it} \tag{16}$$

$\alpha_i =$ Individual constant term,$\beta = slopeparameter$, as well as $\omega_{it} =$ stationary distribution.

3.7 Estimation Techniques

Substantial complications arise in the estimation process in the fixed and random effects settings. The primary difficulty is that the lagged dependent variable is correlated with the disturbance term, even if it is assumed that ε_{it} (equation 10) is not auto-correlated. In this view, fully modified OLS (FMOLS) and Dynamic panel OLS (DOLS) are better techniques to deal with this situation.

3.7.1 Fully Modified Ordinary Least Square Method

The FMOLS and DOLS methods were proposed by Pedroni (2004), respectively. FMOLS method is also considered a non-parametric estimation technique that corrects OLS biases with endogeneity and serial correlation issues among vectors and residuals. Thus, it has fewer assumptions. In this case, FMOLS estimation can be performed with the following equation:

$$\omega_{GM} = N^{-1} \sum_{i=1}^{N} \left[\sum_{t=1}^{T} (\Delta CL_{it} - CL'_i)^2\right]^{-1} \left[\sum_{t=1}^{T} CL_{it} - CL'_i) ED'_i - T\tau_i\right] \tag{17}$$

3.7.2 Dynamic Ordinary Least Square Method

For robustness, we apply the DOLS estimation techniques generated by Pedroni (2004); it is a flexible method owing to allowing the heterogeneous vectors to cointegration within a dimension. Moreover, it is a parametric technique and usually dispersed test which regulates errors during reinforcing stationary regressors by leads and lag values at 1st differences. For example, the following equation can express the DOLS method:

$$ED_t = \gamma_i + CL'_i\beta + d_{1t}\psi_1 \sum_{j=q}^{r} \Delta CL'_{t+j}\delta + \mu_{it} \qquad (18)$$

DOLS and FMOLS produced more reliable estimates.

4. ESTIMATION RESULTS

4.1 Performance towards Energy cleanability

The most common measure of the clean energy gap (ECG) in the suggested evaluation method (TOPSIS) is presented in Table 3. Energy is a crucial component of production, and it has played a critical role in supporting livelihoods and propelling economic growth. The study's findings show that from 2002 to 2015, 55% of the 29 UMIC countries moved towards renewable and clean energy. Also, the amount of electricity produced by oil is constantly decreasing. Furthermore, the ECG indices have fluctuated over time for different countries, so 26% of UMIE has faced the divergence. The reason behind this divergence is that the quality of access to clean energy may significantly impact household behavior in fuel selection, and 19% of countries maintain their 2019 from 2015 ECG score. In this context, UMICs have priorities of economic expansion with the traditional energy-based infrastructure of industrialization. Considering the ECG scores of LMIE, 55%from from 34 showed a little convergence. However, their share of clean energy sources in their aggregate energy share is also meager because many factors affect energy prices, which significantly impact the choice of cooking fuel.

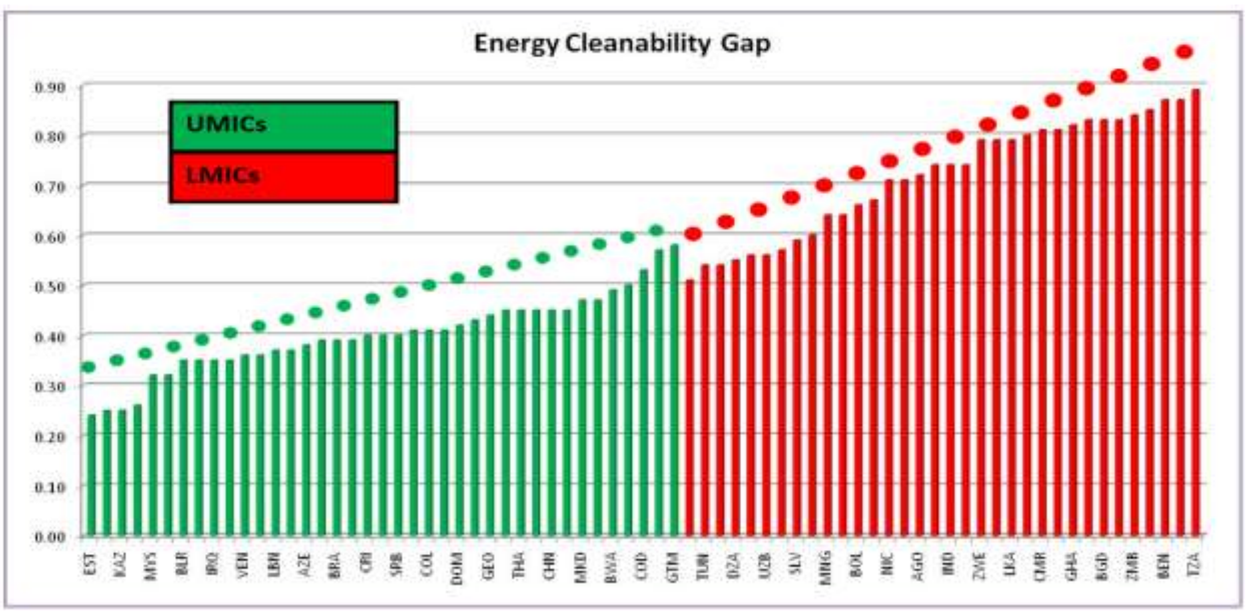

Figure1: Comparison of energy-cleanability gap between low-middle-income & upper middle income countries (Authors' estimation)

The households in Kazakhstan and the Kyrgyz Republic are more inclined to use clean fuels like natural gas since they're situated in areas with abundant gas resources that exist naturally. Furthermore, 34% were kept, while 11% of the LMIE diverged between 2000 and 2015. In addition,t The choice of cooking fuel is influenced by household size. In this way, LMIEs typically have larger households and are more likely to use coal and wood. On the other hand, in urban areas, larger homes are more likely to use electricity and other cleaner fuels as energy input. The figure 1 shows that there is significant difference in the energy cleanability transition gap in selected two panels.

Table 3: Ranks of energy cleanability gap

Code	2000	2005	2010	2015	2019	Code	2000	2005	2010	2016	2019	Code	2000	2005	2010	2016	2019
UMIE																	
RUS	0.32	0.29	0.29	0.25	0.25	CRI	0.43	0.41	0.42	0.41	0.40	THA	0.50	0.48	0.47	0.45	0.45
EST	0.33	0.27	0.26	0.23	0.24	ECU	0.44	0.42	0.41	0.39	0.40	GAB	0.51	0.48	0.47	0.45	0.45
VEN	0.34	0.33	0.34	0.34	0.36	MEX	0.44	0.43	0.43	0.41	0.41	MKD	0.54	0.51	0.50	0.48	0.47
TKM	0.36	0.32	0.30	0.25	0.26	ARM	0.46	0.42	0.41	0.40	0.39	CHN	0.57	0.53	0.49	0.45	0.45
MYS	0.38	0.36	0.34	0.32	0.32	BGR	0.46	0.39	0.39	0.36	0.37	BIH	0.58	0.54	0.50	0.46	0.43
ARG	0.39	0.37	0.37	0.35	0.36	COL	0.46	0.44	0.43	0.42	0.41	BWA	0.58	0.55	0.53	0.51	0.49
BLR	0.39	0.37	0.36	0.34	0.35	DOM	0.46	0.45	0.44	0.42	0.42	ALB	0.59	0.54	0.50	0.46	0.45
TUR	0.39	0.38	0.37	0.35	0.35	AZE	0.47	0.42	0.41	0.38	0.38	GEO	0.59	0.54	0.50	0.45	0.44
JOR	0.40	0.39	0.39	0.38	0.39	IRQ	0.47	0.41	0.39	0.36	0.35	PRY	0.59	0.56	0.54	0.51	0.50
KAZ	0.40	0.33	0.27	0.24	0.25	JAM	0.47	0.44	0.44	0.42	0.41	GTM	0.61	0.60	0.60	0.58	0.58
LBN	0.40	0.38	0.38	0.37	0.37	SRB	0.47	0.45	0.44	0.41	0.40	NAM	0.62	0.60	0.59	0.58	0.57
IRN	0.41	0.37	0.34	0.31	0.32	ZAF	0.48	0.43	0.39	0.36	0.35	PER	0.62	0.55	0.51	0.48	0.47
BRA	0.42	0.41	0.40	0.39	0.39	CUB	0.50	0.48	0.46	0.45	0.45	COD	0.67	0.64	0.61	0.57	0.53
LMIE																	
UKR	0.53	0.50	0.50	0.51	0.51	NIC	0.78	0.76	0.74	0.72	0.71	CMR	0.86	0.85	0.84	0.82	0.81
TUN	0.57	0.56	0.55	0.54	0.54	ZWE	0.78	0.78	0.79	0.79	0.79	COG	0.86	0.85	0.84	0.81	0.81
DZA	0.59	0.57	0.56	0.54	0.55	HND	0.79	0.76	0.74	0.71	0.71	BGD	0.87	0.86	0.85	0.84	0.83
MAR	0.59	0.57	0.56	0.56	0.56	SEN	0.79	0.79	0.79	0.78	0.79	GHA	0.87	0.86	0.85	0.82	0.82
UZB	0.59	0.57	0.56	0.55	0.56	MNG	0.80	0.77	0.73	0.66	0.64	IDN	0.87	0.82	0.75	0.69	0.67
EGY	0.60	0.57	0.56	0.54	0.54	IND	0.82	0.79	0.77	0.74	0.74	KHM	0.88	0.87	0.86	0.84	0.83
MDA	0.66	0.62	0.59	0.57	0.57	PAK	0.82	0.79	0.77	0.75	0.74	BEN	0.89	0.89	0.88	0.87	0.87
BOL	0.67	0.65	0.63	0.67	0.66	CIV	0.83	0.83	0.83	0.83	0.83	KEN	0.89	0.88	0.87	0.85	0.85
SLV	0.70	0.66	0.63	0.60	0.59	LKA	0.84	0.83	0.82	0.80	0.79	NGA	0.89	0.89	0.88	0.88	0.87
KGZ	0.70	0.67	0.64	0.60	0.60	VNM	0.84	0.79	0.73	0.66	0.64	TZA	0.89	0.89	0.89	0.89	0.89
AGO	0.77	0.75	0.74	0.73	0.72	ZMB	0.84	0.84	0.84	0.84	0.84						
PHL	0.77	0.76	0.75	0.74	0.74	NPL	0.85	0.84	0.82	0.81	0.80						

Source: Authors’ calculation

Table 5 shows the variance inflation factor to check the issue of multicollinearity using variance inflation factor is an appropriate process and pursue the standard. But, again, the digit should not be as much as 10, and there is no concern about multicollinearity.

Table 4: Variance Inflation Factor

	ED	CL	R&D	IND	TRD
ED	---				
CL	1.097	---			
R&D	1.520	1.010	---		
IND	1.170	1.091	1.261	---	
TRD	1.003	1.010	1.118	1.031	---

Source: Authors' calculation

All variable results after applying the VIF formula of $(1/(1-r2))$ are below the critical value. Hence, all factors demonstrate that multicollinearity is not problematic in selected variables (see Table 4). Within the line or range of 10, the maximum value of VIF for value in these variables is 1.52. Furthermore, various unit root tests are utilized to analyze the stationary variables to avoid erroneous regression results. Table 5 summarizes the results from the various unit root tests. The unit root test's null hypothesis is "there exists a unit root".

Table 5: Results of unit root tests

Variables	LLC	IPS	ADFF	PPF
HDI	-10.17***	4.12	226.26	856.79***
ΔHDI	-11.14***	-10.24***	541.81***	1324.65***
ECG	-3.37***	-2.60***	160.28***	409.03***
ΔECG	-20.20***	-15.26***	375.43***	589.88***
R&D	-4.00***	-0.87	266.82	304.08**
ΔR&D	-19.07	-19.24***	778.02***	1845.22***
IND	-3.56***	0.63	233.15	284.69
ΔIND	-19.75***	-19.19***	776.57***	1848.70***
TRD	-4.60***	-0.56	248.64	243.11
ΔTRD	-20.52***	-18.33***	820.29***	1523.60***

***, **, * shows significance level at 1%, 5% and 10% respectively (Source: Authors calculation)

The findings suggest that a unit root process exists in the panel at the level and that some variables accept the null hypothesis that they are not stationary at the level. Nonetheless, the findings of the stationarity test show that every model variable is stable at the first difference and satisfies the requirements for threshold regression modeling by disproving the unit root hypothesis. Also, two cointegration tests were used in this study to confirm the long-term relationships between the variables examined. The outcomes are presented in table 6.

Table 6:

Cointegration Test		LMIE	UMIE
		Statistic	Statistic
	Modified Phillips-Perron test	4.79***	6.42***
Pedroni	Phillips-Perron test	-6.36***	-3.02***
	Augmented Dickey-Fuller test	-7.09***	-2.58***
Kao	ADF	-3.99***	-2.21**

***, **, * shows significance level at 1%, 5% and 10% respectively (Source: Authors calculation)

The attained outcomes accept the alternative hypothesis of cointegration significantly in LMIE and UMIE panels. Furthermore, the following analysis stage involved evaluating the long-run elasticities. Therefore, FMOLS & DOLS estimators provided the between-dimension "group mean" and allowed for more flexibility in the presence of heterogeneity problems of the cointegrating vectors. Furthermore, the outcomes of FMOLS models are presented in table 7.

Table 71: Long-run Equation (FMOLS)

Panels	LMIE	UMIE	LMIE	UMIE
Variable	FMOLS		DOLS	
ECG	2.04**	2.75***	3.42***	2.52***
ECG2	-1.80***	-2.35***	-2.78***	-2.24***
R&D	0.03**	0.03***	0.03***	0.05***
IND	0.01	-0.06***	0.02	-0.04***
TRD	0.02	0.02***	0.01	0.02***

***, **, * shows significance level at 1%, 5% and 10% respectively (Source: Authors calculation)

The results obtained from the FMOLS model are presented in table 7. The outcome shows that the energy cleanability gap (ECG) significantly impacts Economic Development (ED). The results show that a 1 unit increase in ECG has to increase ED by 1.82 & 2.59 units in L, LMIE&UMIE panels, respectively. Due to the traditional economic structure, the unclean energy pattern has an encouraging influence on income and employment. Therefore, the current ECG positively impacts income development, benefiting private productivity and consumption. However, the effect of ECG2 on ED is significantly negative. In particular, empirical outcomes demonstrate that a 1% increase in ECG2 has to decrease 1.476 & 2.17 ED in the LMIE & UMIE panel, respectively. The ECG2 negatively impacts health from non-clean energy-based economic activity that reduces aggregate economic outcomes through global feedback Sasmaz et al. (2020). The plots show an in-depth analysis of the quadratic effect of ECG on ED using panel GMM and panel FMOLS and DOLS compared to the post-regression graph.

The 3D plots of GMM provide each combination. The figure 2 & figure 3 shows the curvilinear relationship between energy cleanability gap and sustainable economic development in selected two-panel. Here, it can be observed that an increase in the ECG gap has a quadratic effect on ED in LMIE and UMIE panels. But in the case of ECG squares, it turns down its development, which makes an inverted U-shape curve. After post-estimation from FMOLS and DOLS, the graph depicts the same angle, which is a further robustness check of GMM plots except for the LICs panel.

Furthermore, the development expenditure (R&D) also significantly impacts ED in UMIE. The findings show that a 1% increase in R&D increases 0.02% ED in UMIE. R&D is helping to decrease resource depletion, promoting more sustainable practices, and paving the way to sustainable development. As a result, R&D is seen as having a convergent effect since it offers many benefits, including the conservation of resources, raising living standards, expanding access to goods and services at reduced prices, and providing insights for new sources of income. However, R&D does not impact ED in LMIE because, in this panel, R&D is relatively low; it is crucial to speed up economic development and social values Akhtar, M. J., Rehman, H., & Abbas, Q. (2022).

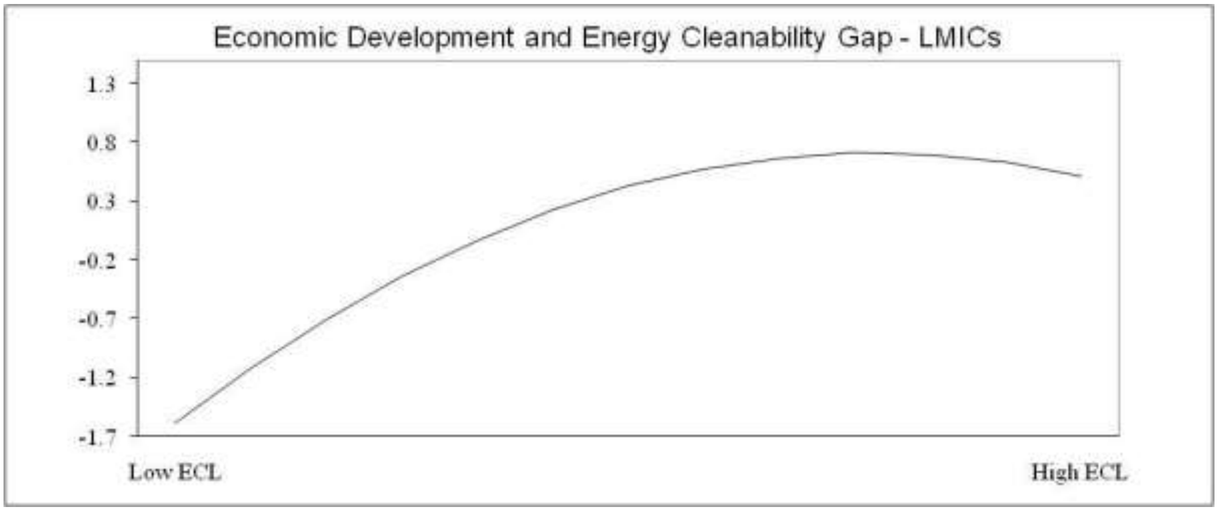

Figure 2: Quadratic Effect of Energy Cleanability on Economic development (Source: Authors calculation)

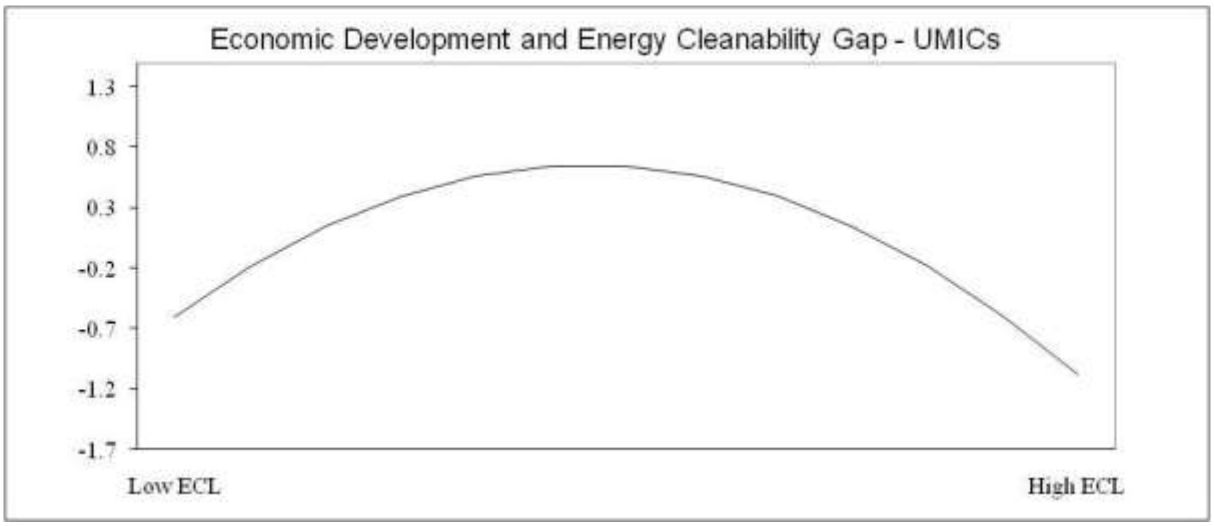

Figure 3: Quadratic Effect of Energy Cleanability on Economic development (Source: Authors calculation)

Furthermore, industrialization (IND) significantly impacts ED in UMIE. Further, a 1% increase in IND has decreased 0.06% ED in UMIE. Therefore, a higher rate of industrialization has increased the demand for unclean energy and significantly impacted health (Hou et al., 2021). Finally, trade liberalization (TRD) has a significant impact: a 1% increase in TRD has increased ED by 0.02 units in UMIE. Therefore, due to TRD, domestic firms can also increase their impact on ED. However, compared to the UMIE, industrial activities and ED is more than the impact in LMIE. These results suggest that TRD, due to technical competence, has not played an essential role in LMIE (Redmond & Nasir, 2020).

5. CONCLUSION AND POLICY IMPLICATIONS

Using data from 73 LMIE & UMIE for 2002–19, this paper examined the empirical evidence of the relationship between dirty energy and economic development. Control variables such as development & research expenditure, industrial value addition, and trade liberalization are employed for the analyses. The panel unit roots tests, panel cointegration, and FMOLS have all been used for this purpose. Using DOLS, it was determined whether the results were robust at each level of the studies. Furthermore, estimated outcomes indicate that the quadratic effect of ECI has a statistically significant impact on economic development with a negative sign in both selected panels. Therefore, an increase in the ECI would have a negative effect on economic development. The long-run dynamics in the proposed model imitate a significantly quadratic effect of ECG on ED in all panels. The result demonstrates that R&D has an incredibly positive impact on ED in UMIE. According to the results, IND has a significantly positive effect on ED in LICs but a negative impact on UMIE panels.

Limitations: The data of ED, ECG, R&D, IND, and TRD of the latest years are missing. These results are estimated with just FMOLS and DOLS econometric techniques. This study considers two income-based panels of 73 economies.

Suggestion: Further research can be extended by applying last year's data of given variables to this model. Further, the empirical analysis can be improved using the latest techniques, such as AMG, CS-ARDL, or DCCE estimation. Finally, the study can be made on different regions and different economies.

Recommendation: The future insight of this study can offer the following essential suggestions. First, the economies should adopt a more effective policy towards energy cleanability with the context of SDGs-2030 to improve the impact on economic development. Second, the development expenditure has a converging impact on sustainable economic development, so it requirs more consistent policy. Third, the industrial sector in UMIE and HICs had a destructive effect on Economic development and should be rearranged. Lastly, pursuing trade liberalization in LMIE, UMIE, and HICs showed a constructive role in Economic development, requiring it to be optimized.

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Federal Tax Revenue Forecasting of Pakistan: Alternative Approaches

ABSTRACT

This study is an appraisal of FBR's existing tax revenue forecasting technique, i.e., the buoyancy approach. It compares the effectiveness of the buoyancy approach and alternative forecasting methods. Using 1984-85 to 2018-19 annual data, predictions are made using different theoretical, statistical, and machine learning methods. The root mean square error (RMSE) suggests that the Least Absolute Shrinkage and Selection Operator (LASSO) and Elastic Net approaches provide better forecasts for total tax and federal excise duty. The Box Jenkins methodology provides the most accurate direct and sales tax estimates, while custom duties are best predicted through the Vector Autoregressive model. On the other hand, mean absolute error (MAE) recommends Marginal Tax Rate (MTR) to forecast all federal taxes of Pakistan. In comparison, the buoyancy approach predictions are not accurate for any of the federal taxes.

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Author's contribution in the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

For decades, forecasting has been used to predict different economic factors. One of them is tax revenue forecasting. Tax receipts are vital to run an economy. Tax revenue1 analysis and forecasting are critical to stabilizing tax and expenditure policy. They play an essential part in annual budget preparation. Predictability provides policymakers and fiscal managers with the data needed to lead borrowing, use accumulated assets, or identify monetary measures to balance the budget. It also notifies about what fiscal arrangements are justifiable and how to balance fiscal policy to curb the complications in the balance of payments and foreign debt.

To augment the timely and compelling analysis of the revenue aspects of the fiscal policy, economies have gradually turned toward domestic tax policy entities rather than depending on tax experts from outside. For example, in the United Kingdom, the Office for Budget Responsibility (OBR), Germany's Federal Ministry of Finance, and in Pakistan the Federal Board of Revenue (FBR) are responsible for projecting the annual estimates of different federal taxes. FBR produces annual forecasts of its tax streams before the budget formulation so that the federal government can plan the expenditures through resource sharing (National Finance Commission-NFC) by the provincial governments. Once the expenditures are set the deficits are estimated and financing options such as Bank borrowing are set.

Every year, there are forecasting errors in Pakistan's federal tax revenues. From 1970 to 2020, the federal government has significant forecast errors for all types of tax revenues. Using 1970-2014 data, two-thirds of the time, total federal taxes were overestimated by more than five percent (Qasim & Khalid, 2016). Errors in tax revenue forecast directly affect budget formulation. The consequences of such errors are misleading tax revenue targets leading to the wrong allocation of resources resulting in arbitrary cuts at the end of the fiscal year such as a cut in development expenditures and/or an increase in the unanticipated debt burden. This, from a policy perspective, has long-run monetary and fiscal effects. A revenue prediction error results in over/underbooking of government expenditures, which, if called back, can result in wastage or under-provisioning. If not adjusted, it would result in extra financing, thus putting pressure on the monetary side as well. Further given Pakistan's federating nature, any revenue prediction error would also carry over to the provinces through the revenue-sharing channel.

The reasons for tax revenue forecasting errors can be administrative, political, or methodological. Unfortunately, the political and organizational issues can't be measured accurately due to the qualitative and dispersed nature of the problems. On the other hand, it is hypothesized that a significant number of these errors may occur due to wrong forecasting methods. The choice of forecasting method plays a vital role in the efficiency of tax revenue forecasting. The inappropriate method would lead to misleading forecasts. FBR uses the Buoyancy approach to forecast tax revenues (FBR, 2021). In this approach, we check the proportionate change in tax revenue with the proportional change in the tax base. The estimates are then multiplied by nominal GDP growth targets.

Several alternative forecasting methods are available for better prediction of revenue streams. In this study, some alternatives to the buoyancy approach are estimated for federal tax revenue forecasts. These methods have been compared to suggest the most accurate predicting method for each federal tax head. Although this study emphasizes methodological and statistical reasons for forecasting problems, administrative constraints can't be ignored entirely. Pakistan has many constraints in terms of forecasting. Every method, data, and parameter is not feasible in all circumstances.

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[1] Tax revenue is the revenue gathered through taxes on any income, profit, social security contributions, goods, and services. It also includes payroll taxes, taxes on ownership, property transfer, and miscellaneous taxes (OECD, 2022).

The paper provides a literature review on alternative forecasting methods, followed by methodology and data description. The results are provided based on alternative methods estimations, followed by conclusion. Limitations and future directions are provided at the end of the paper.

2. LITERATURE SURVEY

There are a large number of methods implemented for tax revenue forecasting across the globe. Each economy forecast taxes considering its economic, social, and organizational indicators. Moreover, academics and researchers have tried many methods that provide better estimates than classical ones. They are divided into theoretical/orthodox methods, statistical methods, and machine learning methods.

2.1. Theoretical/Orthodox Methods

Theoretical or orthodox methods of tax revenue forecasts refer to the methods built specifically for tax forecasting. These are practiced by most economies and also recommended by international economic and financial organizations. Jenkins et al. (2000) provided a brief guide on the importance and practice of tax revenue forecasting. They covered the buoyancy approach, the elasticity method, GDP-based methods, and microsimulation techniques for predicting tax revenues. IMF suggests four methods for tax revenue forecasting; the effective tax rate method, the marginal tax rate method, the elasticity approach, and the regression approach (Firdawss & Karim, 2018). Bayer (2013) described the basic methodology for predicting tax revenues in terms of the macroeconomic approach and from a microeconomic perspective. It also described methods for assessing the quality of predictions.

The theoretical methods are also adopted by some researchers in Pakistan too. Qasim & Khalid (2016) did an accuracy analysis of the tax receipt forecasts in Pakistan. The paper identified that there was a significant difference between the budget estimates of Federal Revenue receipts and actual revenue receipts. They also found that revenue forecasts were as bad after the 1990 reforms as before them. Firdawss & Karim (2018) applied the effective tax rate approach (ETR), marginal tax rate approach (MTR), regression approach, and elasticity approach to forecasting the federal tax revenue of Morocco for the years 2017 and 2018. Gumbo & Dhliwayo (2018) used exponential smoothing, ETR, and elasticity approaches to predict Zimbabwe's VAT revenue for 2012 and 2013. The study found that Exponential Smoothing had relatively lower forecast errors. Some studies in the past also used IMF-recommended regression models. Reed (1983) used two regression models to forecast Indiana's tax revenues. The first model was estimated using two-stage least squares. The second model was an adaptation of the first model.

2.2. Statistical Methods

This section summarizes a literature survey of Statistical tax forecasting techniques. They are categorized as univariate and multivariate methodologies. Univariate approaches involve only one variable, while multivariate approaches involve many variables.

Grizzle & Klay (1994) used the moving average method, the average change method, linear regression, and the curve fitting method to forecast the tax revenue of 28 US states. The fitting method produced the lowest MAPE. Barnard & Dent (1979) demonstrated an econometric model for tax forecasting using ARIMA methods to forecast several exogenous personal income modules. This approach was validated for the State of Iowa. Urrutia et al. (2015) established an ARIMA (0, 1, 0) model to forecast the Income Tax Revenue of the Philippines for the year 2014-2020. Forecasts revealed no significant difference between the actual values of Income Tax Revenue inspected through Paired T-Test. Makananisa (2015) used different time series models to forecast central taxes in the South African Revenue Service. The findings revealed that the SARIMA model accurately predicted personal income tax and value-added tax.

Streimikiene et al. (2018) forecasted the total tax revenue of Pakistan for FY2017 using ARIMA and Vector Autoregressive (VAR) models. The monthly data used for this study was from July 1985 to December 2016. The results confirmed that the ARIMA model did better tax revenue forecasting. Ofori et al. (2020) forecasted Ghana's value-added tax revenue through two methods. The first method was ARIMA with Intervention, and the second method was Holt linear trend method. The findings showed that ARIMA with the Intervention method outpaced the Holt linear trend model in precision. Zaw et al. (2020) used ARMA to forecast tax collection forecasts in Myanmar. The predictions were then compared with the official forecasts of the Myanmar Internal Revenue Department. The results were more accurate than official forecasts. Reed (1983) used the Box-Jenkins methodology to forecast the state tax revenue of Indiana. Nandi et al. (2014) used the Box Jenkins methodology to forecast the total tax revenue of Bangladesh.

Cirincione et al. (1999) scrutinized the impact of the time series estimation method selection, the data length, and the data frequency on forecasting accuracy. The study concluded that exponential smoothing models were the most accurate. Pavlík (2011) focused on forecasting income tax when the time series was short. EGARCH proved to be the best prediction method. Yu et al. (2015) used an error correction mechanism to improve accuracy using a single forecasting model. It forecasted tax revenue using the LS-SVR model with and without ECM. The findings showed that the model with ECM gets superior results to those without ECM. Greoning et al. (2019) used co-integration analysis to recognize factors that affect company tax revenue in Swaziland. Combined forecasting was proven to cause a minor variance one year ahead of the company tax revenue forecast. Molapo (2018) and Molapo et al. (2019) tried to forecast South Africa's primary tax revenue using Autoregressive Moving Averages (ARIMA), the State Space exponential smoothing (ETS) model, and Bayesian Vector Autoregressive (BVAR) model. Based on RMSE, the results proved the superiority of the ETS model.

2.3. Machine Learning Methods

This section reviews machine learning methods used for forecasting, including tax revenues and other variables. Ticona et al. (2017) predicted the income tax revenues of Brazil. This work introduced a hybrid model based on Genetic Algorithms (GAs) and Neural Networks (NNs) for a multi-step forecast of tax revenue collection. The results were more accurate than the outcome that the Federal Revenue of Brazil's Secretariat estimated with the indicators method. Simonov & Gligorov (2020) compared statistical, machine learning, and ensemble methods to forecast the Republic of North Macedonia customs. The study found that neural network autoregression (NNAR) predicted more accurately than statistical and ensemble methodology. Jang (2019) presented an auxiliary tax prediction system that was based on an artificial neural network. The system can help experts to predict tax revenues efficiently.

Waciko & Ismail (2020) used shrinkage methods to forecast and compare the GDP of India and Indonesia. Under the MSE criteria, Elastic Net performed better than LASSO and Ridge Regression. Chung et al. (2022) did revenue forecasting by local governments. Their findings revealed that traditional statistical forecasting methods outperformed ML algorithms overall. But one of the ML algorithms, the k-nearest neighbors (KNN) algorithm, was more effective in predicting property tax revenue. Noor et al. (2022) tested the forecast ability of feed-forward neural networks (FFNN), random forest, and linear regression for tax revenue forecasts in Malaysia. After conducting several experiments, it was found that FFNN achieved the highest accuracy.

The literature survey showed that many tax revenue studies addressing the method issues are available. Most of this research is for advanced economies. An inclusive study of Pakistan's federal tax revenue forecasting errors was needed. There should be research that appraises the methodological issues in the existing federal tax revenue forecasting mechanism. The current system needs better alternatives too. This study will fill this gap.

3. METHODOLOGY

To analyze the different forecasting methods of federal tax revenues, the methodology is divided into three parts theoretical or orthodox methods, statistical methods, and machine earning methods. This exercise will be repeated for different types of federal taxes. Then the accuracy of these methods is judged using root mean square error and mean absolute error. A detailed description of these methods is provided below:

3.1. Theoretical or Orthodox Methods

Theoretical tax revenue forecasting methods involve some fiscal or revenue theory or logic in their estimation. The current study uses the effective tax rate, marginal tax rate, and Buoyancy approaches as theoretical forecasting methods. Following are brief reviews of these methods.

3.1.1. Effective Tax Rate Approach

The effective tax rate (ETR) is the quantity of tax revenue as a percentage of the tax base. While using the ETR, one must consider some factors, like tax evasion and tax exemptions. We can say that a relationship occurs between the tax base and the tax revenue if the ETR is constant over time. Once ETR is established, we can utilize it to forecast tax revenue by multiplying the tax base with the tax rate. But, the forecast is controlled by the trouble of determining the tax base because we need detailed evidence to measure the development of different tax bases. Mainly since these data are not always accessible or published. Even if it is probable to get the tax base for several years, it is not possible to forecast it in every case.

For these causes, IMF suggests a tax base replacement to examine and forecast tax revenue. This tax base can be any economic or financial variable strictly associated with the actual tax base and for which data are obtainable. So, to forecast tax revenue, we first determine the ETR, which is defined as the tax revenue divided by the proxy tax base:

$$Effective\ tax\ rate = \frac{Tax\ revenue}{Proxy\ tax\ base} \tag{1}$$

The forecast of tax revenue is attained by applying the formula given below:

$$Tax(f) = Taxbase(f) * (ETR) \tag{2}$$

Once we determine that the ETR is constant, we can forecast tax revenue by multiplying the forecasted tax base by the tax rate. If the effective tax rate is unstable, it can be replaced by the MTR, i.e., the marginal tax rate (Firdawss & Karim, 2018).

3.1.2. Marginal Tax Rate Approach

The marginal tax rate (MTR) is the ratio of the change in tax revenue to the change in the tax base:

$$Marginal\ tax\ rate = \frac{\Delta Tax\ revenue}{\Delta Proxy\ tax\ base} \tag{3}$$

If the MTR is constant, we forecast the revenues by multiplying the MTR by the forecasted tax base.

$$Tax(f) = MTR * Taxbase(f) \tag{4}$$

This study estimates the marginal tax rate and forecasts for all taxes using equations 3 and 4.

3.1.3. Buoyancy Approach

Tax revenue buoyancy means the total response of tax revenue to change in the tax base or proxy tax base. Buoyancy is given as:

$$Buoyancy = \frac{(\Delta T/T)}{(\Delta GDP/GDP)} \tag{5}$$

And tax revenue forecast through Buoyancy:

$$Tax_f = GDP\ grwoth * Tax\ buoyancy \tag{6}$$

A tax is said to be buoyant if the proportionate change in tax revenue is more than the proportional change in the tax base or GDP. Buoyancy is a desirable property of any tax. It shows the revenue productivity of the tax system. As total income increases, tax revenue automatically follows it (Gumbo & Dhliwayo, 2018). In this study, the method calculates the buoyancies of all tax heads. The buoyancies are then multiplied by nominal GDP growth targets to get the forecasts.

3.2. Statistical Methods

Statistical forecasting methods use statistics to forecast future values based on historical data. These methods involve data and don't care about the economic/ fiscal theory. In this study, a univariate regression technique, i.e., Box-Jenkins methodology, and a multivariate approach, i.e., the Vector-Autoregressive method, are used. In this connection, the literature identifies that multilateral institutions such as the IMF sometimes also use the multivariate regression method to estimate the effect of tax base variables on tax revenue. The accuracy of this method depends on the strength of the relationship between the independent variables (Firdawss & Karim, 2018). Below is the description of both univariate and multivariate methods.

3.2.1. Box-Jenkins Method

The Box-Jenkins method was presented by G. Box and G. Jenkins in their combined book "Time Series Analysis: Forecasting and Control" in 1970. The method starts with the hypothesis that the process that produced the time series can be estimated using ARMA modeling if it is stationary or an ARIMA setting if it is non-stationary. Following Molapo (2018); Streimikiene et al. (2018); Molapo et al. (2019), and Ofori et al. (2020), we have applied the Box-Jenkins method on all federal tax heads.

3.2.2. Vector Autoregressive Method (VAR)

Christopher Sims proposed Vector Autoregressive in 1980. A VAR model is the general/multivariate form of the univariate autoregressive model. It can tackle time series vectors. If the series is stationary, we forecast them using a VAR model to the data straight. If the series is non-stationary, differences in the data are taken to make them stationary. VAR is fitted after that. In these cases, the models are estimated using the OLS.

Another option is that the series is non-stationary and cointegrated. A VAR with ECM term would be included in this case, and alternative estimation methods would be used. Forecasts are recursively produced from the VAR. The VAR model forecasts all variables involved in the system. The study follows Yu et al. (2015) and Greoning et al. (2019) to adopt VAR or VECM for different tax heads.

3.3. Machine Learning Methods

The term 'machine learning' was first used in 1959 by Arthur Samuel, who was at that time working at IBM, and described it as the field of study that allows computers to learn without being explicitly programmed. In this study, we have used three machine-learning techniques to forecast the federal tax heads of Pakistan.

3.3.1. LASSO

LASSO is the acronym for Least Absolute Shrinkage and Selection Operator. It is a statistical formula to regularise data models and feature choices. It is utilized in regression methods for more accurate predictions. It uses the shrinkage technique. Shrinkage is the point where values are shrunk to the mean. This regression is appropriate for models with high multicollinearity levels or when you want to mechanize some parts of model selection, like variable choice/parameter elimination (Chan-Lau, 2017). The mathematical equation of this regression is given as follows:

$$L = \sum_{i=1}^{n}(y_i - \sum_j x_{ij}\beta_j) + \lambda \sum_{j=1}^{p} |\beta_j| \tag{7}$$

Here, λ shows the shrinkage. λ = 0 shows that all features are considered, and it is equal to the linear regression, λ = ∞ shows that no feature is considered. We have used all potential predictors of each tax head revenue. The LASSO automatically chooses the most relevant predictors while minimizing the variance.

3.3.2. Ridge Regression

Ridge regression is also one of the machine learning shrinkage methods. Hoerl and Kennard (1970) proposed Ridge regression. The main difference between LASSO and Ridge regression is that LASSO shrinks the slope to zero while Ridge regression just asymptotically minimizes it close to zero. It is given as follows:

$$R = \sum_{i=1}^{n}(y_i - \sum_j x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{8}$$

The comparison of equations 7 and 8 shows that LASSO regression takes the absolute magnitude of the coefficients, while ridge regression takes the square. For comparison purposes, we have used ridge regression using all potential regressors to get the tax revenue forecasts.

3.3.3. Elastic Net

The Elastic Net Regression method is a convex combination of the Ridge Regression Penalty and the LASSO Penalty. Zou and Hastie developed it in 2005. As the name suggests, it is flexible in adopting the λ value. Elastic Net overcomes the weaknesses of LASSO and ridge regressions as it involves both square and absolute magnitudes of the coefficients. This study follows Waciko & Ismail (2020) in using Elastic Net to forecast tax revenues.

3.4. Evaluation Criteria

These methods' performances are judged based on root mean square error (RMSE) and mean absolute error (MAE).

Table 1: Errors Description and Formulas

Description	Formula
Root Mean Square Error The root mean square error (RMSE) has been used as a standard statistical metric to measure model performance in different social sciences, including Economics.	$RMSE = \sqrt{\frac{\sum(Y_t^p - Y_t^A)^2}{n}}$ Here $Y_t^A = Actual\ Data$ and $Y_t^p = Predicted\ Data$
Mean Absolute Error(MAE) The mean absolute error (MAE) is another useful measure widely used in model evaluations.	$MAE = \frac{\sum \lvert Y_t^p - Y_t^A \rvert}{n}$

For this study, the following variables would be used to assess the accuracy of these tax revenue forecasting methods for Pakistan.

Table 2: Variables Description

Variable	Description
Total federal tax	Total federal tax revenue collection by FBR (million Rs.)
Direct tax	Yearly direct tax revenue collection by FBR (million Rs.)
Custom duties	Yearly custom duties revenue collection by FBR (million Rs.)
Federal excise duty	Yearly federal excise duty revenue collection by FBR (million Rs.)
Sales tax	Yearly Sales tax revenue collection by FBR (million Rs.)
Nominal GDP (CFC)	Nominal GDP measured at current factor cost (million Rs.)
Non-Agr-GDP (CFC)	Non-agricultural GDP measured at current factor cost (million Rs.)
Large Scale Manufacturing	Value addition of Large Scale manufacturing in GDP (million Rs.)
Dutiable Imports	Imports on which duty is leviable (million Rs.)
Total Consumption	Total Consumption expenditure GDP (million Rs.)
Nom-GDP Growth Target	Nominal GDP growth estimate in percentage
Consumer Price Index	Consumer Price index taking base price of 2010
Total Population	Total population of Pakistan
Exchange Rate	PKR to the US. Dollar Exchange rate
Labor	Total Employed Labor

Source: FBR (2021), Economic Survey of Pakistan, World Development Indicators, Annual plans of the Ministry of Planning, Development and Special Initiatives

The data is secondary and yearly from 1984-85 to 2018-19. It is extracted from the official website of FBR, different issues of the Economic Survey of Pakistan, budget documents, annual plans of the Ministry of Planning, Development and Special Initiatives, and the World Bank WDI data set.

4. ANALYSIS OF DATA

As discussed in the methodology section, all types of methodologies are applied to different types of federal taxes. i.e., total tax, direct tax, sales tax, customs duties, and federal excise duty. The root mean square error and mean absolute error for all eight forecasting methods are discussed in this section. In this section, ways are mentioned in the form of abbreviations.

4.1. Total Tax

In table 3, according to root mean square error (RMSE), Least Absolute Shrinkage and Selection Operator (LASSO), and Elastic Net provide the best total tax revenue forecasts with a minimum error of 0.03. On the other hand, mean absolute error (MAE) suggests Marginal Tax Rate (MTR) as the best forecaster with an error of 0.016. The results deny Streimikiene et al. (2018). They found out that Box Jenkins provided better predictions for FY17 for Pakistan.

Table 3: Statistical Errors for Total Tax Forecasting Methods

Estimation Methodology	RMSE	MAE
Buoyancy Approach	0.108	0.093
Box Jenkins	0.05	0.036
Vector Autoregressive Model	0.063	0.051
Elastic Net	0.031	0.025
LASSO	0.031	0.024
Ridge Regression	0.046	0.038
Effective Tax Rate	0.118	0.095

Marginal Tax Rate	0.751	0.016

Source: Authors' calculations

4.2. Direct Tax

According to table 4, root mean square error (RMSE), with a value of 0.089, suggests that Box Jenkins methodology provides the most accurate forecast for direct tax. On the other hand, mean absolute error (MAE) recommends Marginal Tax Rate (MTR) as the best method to forecast direct tax with an error value of 0.025.

Table 4: Statistical Errors for Direct Tax Forecasting Methods

Estimation Methodology	RMSE	MAE
Buoyancy Approach	0.15	0.09
Box Jenkins	0.089	0.067
Vector Autoregressive Model	0.102	0.074
Elastic Net	0.098	0.077
LASSO	0.098	0.077
Ridge Regression	0.102	0.075
Effective Tax Rate	0.149	0.128
Marginal Tax Rate	1.434	0.025

Source: Authors' calculations

4.3. Sales Tax

Table 5 shows that according to RMSE, Box Jenkins provides the most accurate sales tax forecasts with an error of 0.088. On the other hand, MAE suggests that the Marginal Tax Rate (MTR) approach is the most efficient technique, with an error of 0.019.

Table 5: Statistical Errors for Sales Tax Forecasting Methods

Estimation Methodology	RMSE	MAE
Buoyancy Approach	0.196	0.159
Box Jenkins	0.088	0.073
Vector Autoregressive Model	0.122	0.092
Elastic Net	0.102	0.079
LASSO	0.101	0.078
Ridge Regression	0.107	0.082
Effective Tax Rate	0.16	0.117
Marginal Tax Rate	0.896	0.019

Source: Authors' calculations

4.4. Custom Duties

According to table 6, the customs duties of Pakistan are best forecasted through the Vector Autoregressive model with a root mean square error (RMSE) of 0.114. In contrast, the mean absolute error (MAE) value of Marginal Tax Rate (MTR) is minimum, i.e., 0.046 proving it the most appropriate method to forecast custom duties.

Table 6: Statistical Errors for Custom Duties Forecasting Methods

Estimation Methodology	RMSE	MAE
Buoyancy Approach	0.204	0.142
Box Jenkins	0.157	0.124
Vector Autoregressive Model	0.114	0.091
Elastic Net	0.128	0.093
LASSO	0.128	0.093
Ridge Regression	0.130	0.097

Effective Tax Rate	0.248	0.174
Marginal Tax Rate	2.500	0.046

Source: Authors' calculations

4.5. Federal Excise Duty (FED)

According to table 7, the Least Absolute Shrinkage and Selection Operator (LASSO) and Elastic Net have a minimum root mean square error (RMSE) of 0.089. In contrast, Marginal Tax Rate (MTR) has a minimum mean absolute error (MAE) of 0.033 while forecasting the federal excise duty of Pakistan. According to these errors, LASSO, Elastic Net, and MTR are more appropriate to predict federal excise duty (FED) than any other method.

Table 7: Statistical Errors for FED Forecasting Methods

Estimation Methodology	RMSE	MAE
Buoyancy Approach	0.121	0.090
Box Jenkins	0.115	0.101
Vector Autoregressive Model	0.109	0.094
Elastic Net	0.089	0.072
LASSO	0.089	0.072
Ridge Regression	0.090	0.075
Effective Tax Rate	0.167	0.142
Marginal Tax Rate	1.609	0.033

Source: Authors' calculations

5. CONCLUSION

Revenue forecasting is important because the government needs an accurate value for fiscal policy. Any forecast error would lead to mismanagement in fiscal policy operations. It will lead to government expense cuts if revenue forecasts are biased upwards. If the expenditures are not cut, it will have an unanticipated increase in debt raising for deficit financing. For countries where there are federating setups and revenues are collected at the center and then distributed at the government's lower tiers, the revenue forecast errors further exacerbate the mismanagement in fiscal policy operations as it now runs in all governments.

Pakistan is a federation in which the resources are collected at the center and then shared through the revenue sharing formula (NFC award). So any forecast error for revenue stream would result in mismanaged fiscal operations, mistargeting targets, or additional debt burdens. Therefore it is imperative to evaluate and propose alternative methods of forecasts for federal taxes in Pakistan. As studies have noted (Qasim and Khalid, 2016) that revenue forecasting errors are significant. This may be due to other reasons, but for this study, we have focused on evaluating different methods of forecasting to propose an alternative but better methods for different federal tax streams.

The forecasting is done using alternative theoretical, statistical, and machine-learning methods. The RMSE suggests that LASSO and Elastic Net are the best choices to forecast total tax and FED. Box Jenkins predicts accurately while forecasting sales tax and direct tax. Customs duties are better predicted through VAR. On the other hand, MAE suggests the marginal tax rate approach as the most appropriate forecasting method for all taxes. According to the results, it is evident that method revision can play a vital role in improving Pakistan's federal tax revenue forecasting.

6. LIMITATIONS AND FUTURE DIRECTIONS

In this study, the statistical losses of forecasting methodologies are calculated in terms of MAE and RMSE. Future studies can also calculate the statistical accuracy in terms of biasedness and comprehension of the method. Other statistical accuracies like asymmetrical statistical loss function can also be calculated. The study has not focused on the political and administrative side of tax revenue forecasting. Future studies can incorporate these aspects.

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Banks Efficiency Analyses in Dual Banking System

ABSTRACT

The share of Islamic banks is growing in the banking sector steadily. An increasing number of conventional banks are introducing Islamic banking services. We estimate the efficiencies of banks by applying Data Envelopment Analysis (DEA) and for bias correction, we apply the double bootstrap method. In the second stage, determinants of efficiency are analyzed. Annual data from the reports of the banks is employed for the analysis Conventional banks providing Islamic banking services are found to be performing better in terms of technical efficiency than pure Islamic and pure conventional banks. In the financial crisis period, there is no evidence of a difference in the performance of banks across all groups.

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1. INTRODUCTION

Banking is a major sector in the financial industry of an economy. It plays a role of a mediator between the fund suppliers and fund demanders. Islamic banking has shown steady growth in capturing its share of the financial system. Most Islamic banks are performing in dual banking systems of countries. In the financial crisis of 2008, many conventional banks faced difficulties. The Islamic banking industry was largely not that affected by the crisis (Yilmaz, 2009; Willison, 2009; Hasan & Dridi, 2011).

This study aims to analyze the performance of Islamic and conventional banks in Pakistan from 2003 to 2010. Banks are a significant part of the financial sector in Pakistan. There is an increasing number of conventional banks which are introducing Islamic financial services. Therefore, it is necessary to account for those banks. We will address these banks as hybrid banks in this paper.

The performance of the banks is commonly measured by estimating their efficiency. Efficiency refers to the maximizing of output in a way that minimizes the inputs. The optimal quantity would be the possible combinations of inputs and outputs that a specific bank can achieve under output maximization or input minimization conditions (Wheelock & Wilson, 1995). In this paper, we estimate the technical efficiencies of the banks. According to (Berger & Humparey, 1997), there can be three parametric approaches and two non-parametric approaches to measuring the technical efficiency of financial institutes. The three parametric approaches are the Stochastic Frontier Approach (SFA), the Distribution Free Approach (DFA), and the Thick Frontier Approach (TFA). The non-parametric approaches are Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). The most widely used approach is DEA. Five approaches to defining the inputs and the outputs can be found in the literature: intermediation, production, asset, value-added and user cost. Most of the frontier studies in banking have adopted the intermediation approach, and some have used the production approach. To evaluate the entire bank's performance Berger and Humphrey (1997) suggested the intermediation approach be the best. Butt et al. (2018) investigated the perceptions of people and found that people do not believe the Islamic banking to be completely interest free.

The present study uses the non-parametric approach Data Envelopment Analysis (DEA) and intermediation approach to measure the efficiencies of banks. We apply the two-stage double bootstrap DEA of Simar and Wilson (2007). This approach enables us to overcome the issue of the non-statistical nature of simple DEA. In the second stage following the same approach, we analyze the environmental variables affecting the estimated efficiency score. Previous studies on this topic have not used the double bootstrap approach therefore may have biased results.

An efficiency comparison of Islamic banks working in the dual banking system would provide insights into their performance. The introduction of Islamic banking services by the already existing conventional banks has increased the competition for Islamic banks. There has been no study that considers hybrid banks as a separate group of banks. Mokhtar et al. (2006) consider only the Islamic windows of conventional banks and compare them to Islamic banks. As more and more conventional banks are offering Islamic banking products, we think it is viable to consider them separately as a full banking entity, not just their Islamic window in the efficiency analysis of the banking sector. As the introduction of Islamic banking services is likely to influence the whole operations of the banks, these hybrid banks may have more trust of the people as they have already established their reputation. It is also possible that people may not take them as Islamic banks and they lose trust.

The specific objectives of the study can be stated as:

- Determine the efficiency of all three groups of banks operating in Pakistan.
- Comparing the efficiencies across groups and bank sizes.
- Determining the impact of environmental variables on the efficiencies of all the groups.

The value added to this paper would be that it covers the whole lifetime of Islamic banks in Pakistan, so the results are more reliable. The hybrid banks introduced in this study are not used in any other study to the best of the author's knowledge. We use bank age and the number of branches to measure the impact of environmental variables on the efficiency of the banks.

The rest of the paper is structured as follows: section 2 gives a brief literature review on Islamic banks' efficiencies, section 3 discusses the methodology, and section 4 gives the details of the data used for the study. Results are discussed in section 5 and section 6 concludes the discussion.

2. LITERATURE REVIEW

Islamic banks are increasing their share in the banking industry consistently over the last few decades. Researchers are interested to compare the two banking systems from different aspects. The findings vary across the papers. On the one hand, some studies suggest Islamic banking to be more efficient and consistent than conventional banks, and others have findings opposite to this.

The nonparametric programming approach DEA used in this study to estimate the technical efficiency, and their changes over time is based upon the work of Farrell (1957). Based on the idea given by Farrell (1957), the DEA technique was introduced by Charnes et al. (1978) to estimate the technical efficiency of a unit under input orientation and constant returns to scale (CRS). Banker et al. (1984) extended the DEA technique to allow variable returns to scale (VRS). In a literature review study of 130 research papers Berger and Humphrey (1997) concluded that almost half of these studies used this approach. They also found that the average efficiency of banks is 77% average and the median is 82%, however, the statistics are significantly different across countries.

Chowdhury et al. (2021) in a study of Islamic banks of Southeast Asia concluded that efficiencies of these banks improved but still various inefficiencies are reported. Sufian et al. (2008) estimated efficiencies for 16 banks in the Middle East, North Africa, and Asia. They concluded that the efficiency of Islamic banks decreased from 2001 to 2003, increased in 2004, and again decreased in the years 2005 and 2006. Iranian banks were the most efficient banks and banks in Sudan and Gambia were found to be operating at relatively low efficiency. Analyzing 18 Islamic banks from 12 countries, through the DEA approach, Yudistira (2004) claimed that the overall efficiency of Islamic banks is very low i.e. about 10%. Islamic banks suffered but performed well after the crises of 1998-99. Middle Eastern banks showed less efficiency.

Samad and Hassan (1999) evaluate one Malaysian Islamic bank for risk and profitability with a group of conventional banks for the period 1984 to 1997. Islamic banks turned out to be less risky and the economic participation in the economy is the same for both types of banks. Mokhtar et al. (2006) estimated the efficiency of Islamic banks, Islamic windows, and conventional banks in Malaysia. The cost and technical efficiency of Islamic banks are lower but have improved more than the other counterparts. Islamic banks have higher costs and technical efficiencies as compared to Islamic windows.

Čihák and Hesse (2010) compared Islamic and conventional banking systems in different countries. They stated that large conventional banks are financially stronger than large Islamic banks, but small Islamic banks tend to be financially stronger than small conventional banks. Chong et al. (2009) argued that Islamic banks as practiced in Malaysia are not much different from conventional banks therefore for analysis should not be treated differently. Kassim et al. (2009) analyzed the impact of monetary policy shocks on conventional and Islamic banks in Malaysia through the impact of interest rate changes and found Islamic banks to be more sensitive to these shocks.

Parashar and Venkatesh (2010) analyzed the global financial crisis impact on the Islamic banking sector in GCC (Gulf Cooperation Council) countries and compared the two banking systems using five performance criteria. Islamic banks were found to be better in profitability but they suffered more in terms of the leverage ratio and capital adequacy as compared to conventional banks. Conventional banks suffered more in liquidity though. Srairi (2010) employed the stochastic frontier approach to investigate the cost and profit efficiency of Islamic and conventional banks in Gulf cooperation council countries. The results suggest on average Islamic banks are less efficient than their conventional counterparts. Saaid et al. (2003), and Shahid et al. (2010) also estimated the technical, profit, and cost efficiencies of Islamic and conventional banks for Sudan and Pakistan, and found Islamic banks to be less efficient. Hassan (2006) also got the same results of Islamic banks being less efficient for the analysis of 43 banks in 21 countries for the years 1994 to 2001.

Johnes et al. (2014) applied the DEA approach to Islamic and conventional banks in 18 countries. Their results conclude that both types of banks are performing similarly at gross efficiency scores. However Islamic banks are significantly higher in net efficiency and lower in type efficiency. The second stage analysis also seconds the results. Beck et al. (2013) found few significant differences in the business orientation of Islamic and conventional banks. Islamic banks are less cost-efficient but are better in intermediation ratio and are better capitalized. Large cross-country variations and size differences are found in the efficiencies of Islamic and conventional banks.

Islamic banks are less risky and capitalized better than there conventional counterparts, but profits of Islamic banks are estimated to be lower than the others (Majeed et al., 2021). Islamic banks are less efficient than conventional banks, and the Islamic branches of conventional banks are efficient than conventional branches (Majeed et al., 2016).

3. METHODOLOGY

In the present study, Data envelopment analysis (DEA) is used to estimate the technical efficiency (TE) scores. Data Envelopment Analysis (DEA) is a non-parametric approach to measuring the efficiency of decision-making units. In the relative measurement of the performance of banks, DEA is commonly used. Based on the idea given by Farrell (1957), the DEA technique was introduced by Charnes et al. (1978) to measure the efficiency of decision-making units under input orientation and constant returns to scale (CRS). Banker et al. (1984) extended the DEA technique to allow variable returns to scale (VRS).

DEA is a linear programming-based approach to measuring the efficiency of firms where there are multiple inputs and outputs which makes the comparison difficult. This approach uses the values of input and outputs to determine an efficiency frontier that envelops all the existing data points. Firms lying on the frontier are considered to be the most efficient ones. It gives a score of 1 to fully efficient firms and 0 to fully inefficient firms. The most efficient firm or firms does not necessarily mean that they are generating the maximum output level, but it indicates that it tends to produce best practice output among the given sample of firms.

We use the input-oriented approach under variable returns to scale for the estimation of TE:

$$\hat{\theta}(u,v) = max\{\theta | \theta v \leq \sum_{i=1}^{n} \lambda_i v_i\, ; u \geq \sum_{i=1}^{n} \lambda_i u_i\, ; \sum_{i=1}^{n} \lambda_i = 1;\ \ \lambda \geq 0\ \ , i = 1, \dots, n\} \qquad (1)$$

where u_i is a vector of inputs, v_i is a vector of output, and λ_i is an $N \times 1$ vector of constants. The obtained value of $\hat{\theta}_i$ will be the technical efficiency of the ith bank. A value of $\hat{\theta}_i = 1$ represents that the bank is efficient and $\hat{\theta}_i > 1$ will be the indicator of inefficient banks. The value 1/ $\hat{\theta}_i$ will define the technical efficiency score, which ranges from 0 to 1. This linear programming problem is solved n times, once for each bank. For detailed literature on this method refer to Coelli et al. (1998) and Fried et al. (2008).

As the method of DEA is a linear programming method, the issue of the statistical limitation of DEA has been raised. The estimated scores strongly depend on each other and may generate biased results. Simar and Wilson (1998, 1999) suggested a “bootstrap” method to overcome this issue and to generate good statistical properties of the efficiency scores. Bootstrap is a resampling method to obtain the statistical properties of a variable of interest. It generates a sampling distribution by mimicking the data generation process. We assume our original sample data is generated by a data-generating process and we can simulate this process by taking a pseudo data set, which is drawn from the original data set. By using this new data set we re-estimate DEA and repeat this 2000 times, which gives us a Monte Carlo approximation of the sampling distribution and helps the inference procedure

We also extend the analysis for the impact of the environmental variable on efficiency. A common approach is to use Tobit regression to estimate the impact of these control variables on the obtained technical efficiency. Simar and Wilson (2007) emphasized using a double bootstrap approach to improve the accuracy of the estimates of regression and also construct confidence intervals for efficiency scores. The regression model would be

$$\hat{\theta}_i = z_i\beta + \varepsilon_i \tag{2}$$

where z_i is a vector of environmental variables that can affect the efficiency of banks in our sample. Here β refers to a vector of parameters, ε_i denotes a noise term. The use of Ordinary Least Squares (OLS) may lead to estimation problems of correlation and endogeneity of the efficiency score, which violate the assumption of ε_i to be independent of z_i. The double bootstrap procedure of Simar and Wilson (2007) is illustrated as follows:

1. Using the original data compute $\hat{\theta}_i = \hat{\theta}(u_i, v_i), i = 1, \dots, n,$ by using the linear programming problem in equation (1).
2. Using the method of maximum likelihood obtain the estimates of truncated regression in equation (2), $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$.
3. Loop the next 4 steps (a to d) L1 times to obtain a set of bootstrap estimates.
$$\theta^*_{i,l}(u_i, v_i), l = 1, \dots, L1$$
    a. Draw ε_i^* from the $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation (1- $\hat{\beta}$ $_{z_i}$).
    b. Compute $\theta_i^* = \hat{\beta} z_i + \varepsilon_i^*$, $i = 1, \dots, n$
    c. Construct a pseudo data set by setting $u_i{}^* = u_i$, $v_i^* = v_i\hat{\theta}_i/\theta_i{}^*$, for all , $i = 1, \dots, n$
    d. Compute $\hat{\theta}_i{}^* = \theta(u_i, v_i), i = 1, \dots, n$, by replacing (u_i, v_i) by $(u_i{}^*, v_i^*)$.
4. For each $i = 1, \dots, n$, compute the bias-corrected estimator by using bootstrap estimates and original estimates. $\hat{\hat{\theta}}_i = \hat{\theta}_i - bias(\hat{\theta}_i)$
5. Use the maximum likelihood method to estimate the truncated regression of $\hat{\hat{\theta}}_i$ on z_i, yielding $(\hat{\hat{\beta}}, \hat{\hat{\sigma}})$.
6. Loop over the next three steps (a to c) L2 times to obtain a set of bootstrap estimates.
7. $\left(\hat{\hat{\beta}}_l^*,\ \hat{\hat{\sigma}}_l^*,\quad l = 1, \dots, L2\right)$.
    a. For each $i = 1, \dots, n$, ε_i is drawn from $N(0, \hat{\hat{\sigma}})$ with left truncated regression at $(1 - \hat{\hat{\beta}}\ z_i)$.
    b. For each $i = 1, \dots, n$, compute $\theta_i^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i^{**}$.
    c. Use the maximum likelihood to again estimate the truncated regression of θ_i^{**} on z_i to yield estimates$(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$.
8. Construct confidence intervals by using the bootstrap efficiency scores.

4. DATA

To measure the efficiency of Islamic banking, data from 6 Islamic banks, 11 conventional banks providing Islamic banking, and 18 pure conventional banks are used. Unbalanced yearly panel data is available for the period 2003 to 2010. The main sources for the variables used in this study are various editions of Banking Statistics of Pakistan (published annually), annual and quarterly financial reports of the individual banks, the Economic survey of Pakistan, and International Financial Statistics. A detail of the variable is given in Table 1. The year-by-year breakdown of the banks in three categories is given in Table 2.

Table 1: Description of the variables

Variables	**Notations**	**Names**
Inputs	X1	Labor
	X2	Assets
	X3	Borrowing and deposits
	X4	Admin and other expenses
Outputs	Y1	Loans and advances
	Y2	Investments
Environmental	RE	Return on Equity
	RA	Return on Assets
	EI	Total Expenses to total income
	EA	Earning assets to total assets
	EE	Earning per employee
	AG	Bank age
	BR	Number of branches
	AT	Number of ATM
	DI	Dummy for Islamic banks
	DC	Dummy for Conventional banks
	DH	Dummy for Hybrid banks

Table 2: Year-wise number of banks

Types of the Banks	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Islamic Banks	2	2	2	4	6	6	6	5
Hybrid Banks	3	4	6	10	10	10	11	11
Conventional Banks	21	22	21	20	20	20	18	18
Total	26	28	29	34	36	36	35	34

5. RESULTS

5.1 Efficiency

We estimated the efficiency scores for the banks included in our sample through the double bootstrap method discussed in section 3.

Table 3 contains the mean and standard deviations of the inputs and outputs used to estimate the efficiency scores from the years 2003 to 2010. The average loans and advances (Y1) have increased from 6.69 billion rupees to 28.99 billion rupees for Islamic banks from the year 2003-2010. The increase is steady except for the year 2006 when it decreased. A similar kind of trend in loans and advances is observed for hybrid banks i.e. an increase from 56.97 billion to 217.90 billion at the same time, whereas the conventional banks have not shown this trend. Their loans and advances remain almost constant over the period with little variation. Islamic banks have also shown a steady increase in output Y2, from 0.78 billion to 19.06 billion for the period 2003-2010. Hybrid banks show an increasing trend overall except for two years and their investments increased from 30.90 billion to 142.35 billion for the sample period. As of output Y1, the conventional banks have not shown any specific trend overall and decreased from 24.14 billion to 17.92 billion over the sample period.

For average inputs, i.e. labor, assets, borrowings/deposits, and admin expenses, an overall increasing trend has been observed for the Islamic and hybrid banks. For conventional banks, these input factors are nearly constant over the years, in some cases, they even show a decrease.

The year-wise individual estimated efficiency scores for the three types of the bank are presented in Appendix. These tables contain raw efficiency scores, bias-corrected efficiency scores, and confidence intervals, which we estimated by applying the methodology described in section 3.

Table 3: Descriptive statistics of banks (in billion Rupees, except X1: labour)

Years	Banks	Descriptive	Loans/adv (Y1)	Investment (Y2)	Labor (X1)	Assets (X2)	Borr/dep (X3)	Ad.ex (X4)
2003	Islamic Banks	Mean	6.69	0.78	206.50	0.46	8.45	0.20
		Std. Dev	1.00	0.62	44.55	0.44	0.42	0.09
	Hybrid Banks	Mean	56.97	55.57	4250.00	5.46	116.80	3.23
		Std. Dev	50.50	63.70	5258.93	5.13	116.23	3.83
	Conventional Banks	Mean	40.15	24.14	2916.29	3.76	72.30	1.87
		Std. Dev	59.58	49.02	4987.09	7.01	118.84	2.95
2004	Islamic Banks	Mean	9.67	0.92	358.00	0.90	13.19	0.29
		Std. Dev	3.78	0.72	216.37	0.93	4.87	0.17
	Hybrid Banks	Mean	69.57	30.90	3643.50	6.11	109.11	2.77
		Std. Dev	61.88	27.08	4365.70	6.09	95.58	3.29
	Conventional Banks	Mean	49.47	20.07	2838.45	4.17	81.31	2.07
		Std. Dev	74.60	41.62	4946.02	7.25	133.88	3.52
2005	Islamic Banks	Mean	13.58	0.85	519.00	1.39	18.76	0.47
		Std. Dev	8.71	1.07	377.60	1.60	9.89	0.35
	Hybrid Banks	Mean	127.23	45.77	6532.33	9.77	182.17	4.58
		Std. Dev	116.32	37.14	6527.86	8.91	160.54	5.04
	Conventional Banks	Mean	48.57	17.56	2728.81	4.14	72.00	1.82
		Std. Dev	76.93	36.06	4336.17	7.55	118.82	2.93
2006	Islamic Banks	Mean	11.64	1.35	625.25	1.47	15.15	0.56
		Std. Dev	13.18	1.06	529.09	1.04	16.85	0.42
	Hybrid Banks	Mean	168.51	55.98	7975.40	14.41	240.72	6.38
		Std. Dev	124.77	43.81	6497.87	12.69	179.75	5.95
	Conventional Banks	Mean	28.83	8.75	1440.95	2.54	39.40	1.09
		Std. Dev	43.40	12.30	2107.02	3.66	56.94	1.40
2007	Islamic Banks	Mean	13.39	3.69	763.50	1.88	18.15	0.77
		Std. Dev	15.19	3.51	764.64	1.36	19.98	0.67
	Hybrid Banks	Mean	182.20	86.92	8115.30	21.00	281.49	7.34
		Std. Dev	136.28	67.80	5894.86	18.76	212.59	6.26
	Conventional Banks	Mean	36.90	16.21	1824.40	4.91	54.32	1.42
		Std. Dev	50.76	24.01	2492.10	8.35	76.36	1.62

Table 3: (Continued) (in billion Rupees, except X1: labour)

Years	Banks	Descriptive	Loans/adv (Y1)	Investment (Y2)	Labor (X1)	Assets (X2)	Borr/dep (X3)	Ad.ex (X4)
2008	Islamic Banks	Mean	19.07	4.71	1117.33	2.65	24.91	1.25
		Std. Dev	19.67	4.87	1047.04	1.90	25.19	0.86
	Hybrid Banks	Mean	216.50	75.68	8492.00	25.89	310.79	9.46
		Std. Dev	164.35	53.76	5909.55	21.98	233.84	7.71
	Conventional Banks	Mean	40.58	12.05	2031.85	6.45	55.60	2.21
		Std. Dev	57.16	19.36	2694.65	9.28	79.11	2.49
2009	Islamic Banks	Mean	25.43	6.81	1387.33	3.42	35.49	1.65
		Std. Dev	26.63	8.26	1159.65	2.64	36.81	1.06
	Hybrid Banks	Mean	208.05	111.20	7871.09	26.31	335.45	9.90
		Std. Dev	162.73	67.22	5578.66	25.26	243.93	8.06
	Conventional Banks	Mean	33.57	15.82	1788.28	6.05	52.30	2.09
		Std. Dev	61.62	24.94	2859.48	10.34	86.98	2.35
2010	Islamic Banks	Mean	28.99	19.06	1721.20	4.01	54.56	2.24
		Std. Dev	21.19	20.60	1509.46	1.62	48.14	1.35
	Hybrid Banks	Mean	217.90	142.35	7934.82	28.48	375.58	11.24
		Std. Dev	164.82	93.10	5285.68	24.15	270.83	8.83
	Conventional Banks	Mean	34.17	17.92	1645.33	3.76	54.92	2.29
		Std. Dev	60.89	29.91	2875.76	4.04	90.84	2.96

Table 4: Bias-corrected average efficiency scores 2003-2010

Type of Banks	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Islamic Banks	0.775	0.748	0.783	0.784	0.719	0.812	0.804	0.755
Hybrid Banks	0.964	0.858	0.858	0.884	0.926	0.907	0.909	0.918
Conventional Banks	0.823	0.776	0.821	0.771	0.849	0.837	0.840	0.826

As we are interested in comparing the efficiency scores of three groups of banks over the sample period, table 4 presents the average bias-corrected efficiency scores. The efficiency of the hybrid banks is relatively higher than that of the Islamic and conventional banks over the sample period. The efficiency of Islamic banks was 0.775 in 2003, remained almost the same till 2006, and decreased in 2007 to 0.719, it may have happened because of the new Islamic banks entering the market.

Figure 1 presents the graphical representation of the results. We can see in the figure that except for the year 2007, all the bank groups are showing a similar trend. After 2008 efficiency declined and almost by the same ratio for all three types of banks. In 2010 the banks again show an increase in efficiency except for Islamic banks which it shows a small decrease.

Figure 1 shows that HBs are outperforming the other two types of banks in terms of efficiency in almost all years. To understand whether this difference is statistically significant, we perform a pairwise comparison of the banks (Figures 2 to 4). Here we calculated CI for the efficiencies of average banks, which we calculated by adding the three average banks in our DEA calculations of the banks (year-wise table in Appendix). Non-overlapping 95% confidence intervals mean that differences are significant at the 10% level (Bonferroni correction, Bonferroni. 1936).

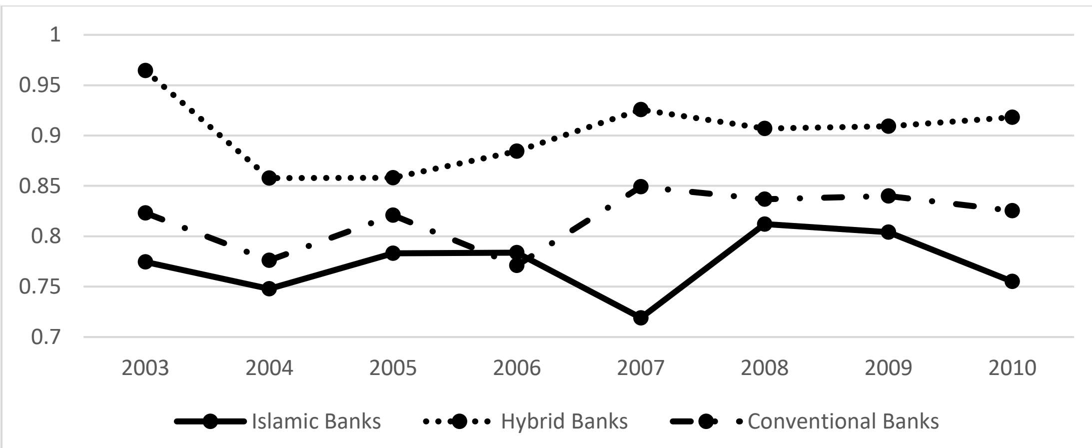

Figure 1: Bias-corrected average efficiency scores 2003-2010

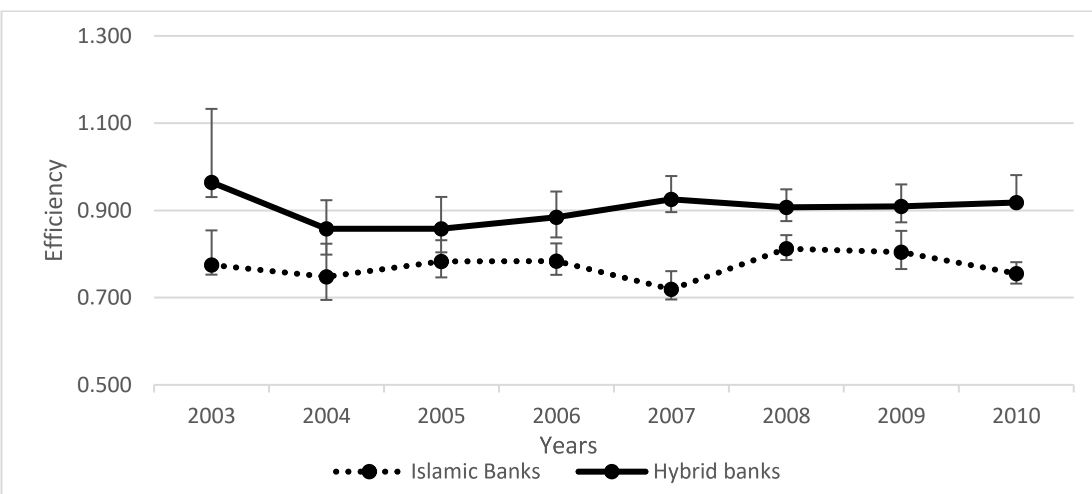

Figure 2: Comparison of efficiency among Islamic and Hybrid banks

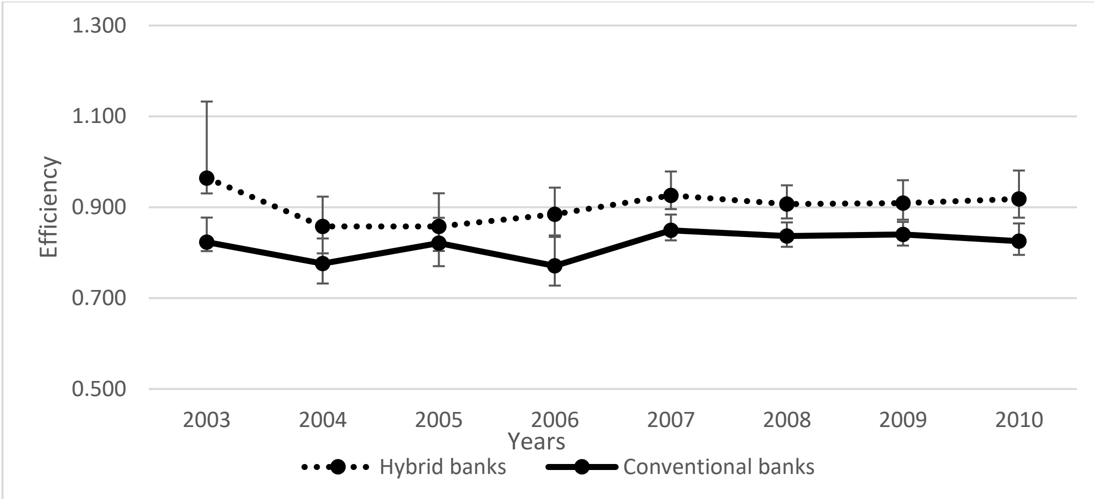

Figure 3: Comparison of efficiency among Conventional and Hybrid banks

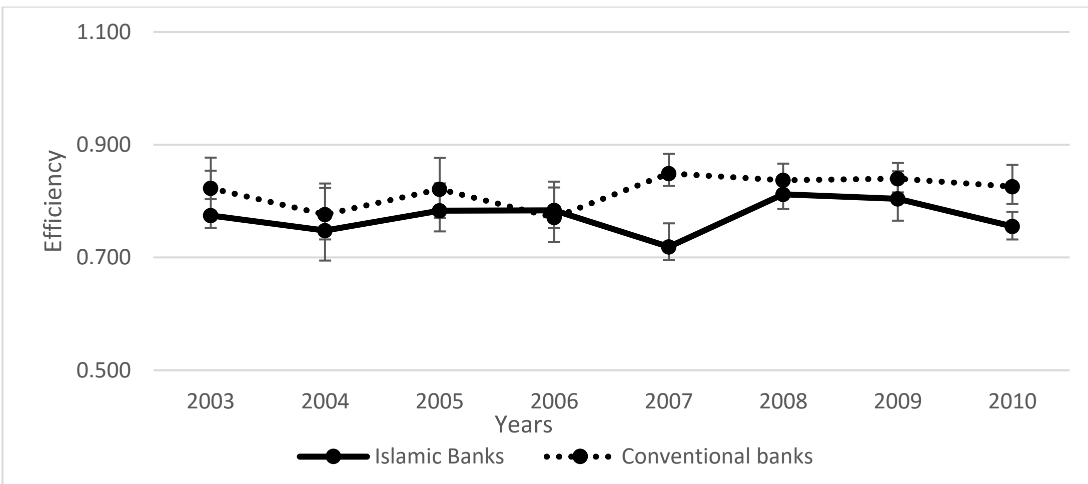

Figure 4: Comparison efficiency among of Islamic and Conventional banks

Figure 2 shows the average efficiencies of IB and HB. Here we can see that except for two years, the CI is not overlapping, and hence we can say that for most of the years, the difference between the efficiencies scores of both groups of banks is statistically significant at the 10% level. From figure 3 we can see that for Conventional and Hybrid banks, the CI are overlapping for three years from 2004 to 2006 and for the rest of the years there is a statistical difference in the efficiency scores of the two groups. From figure 4 it is clear that when we compare Islamic banks to conventional banks then we only see 2 years where the CI of the efficiency scores are not overlapping, for the rest of the years we can easily say that there is no statistical difference in their efficiency scores of both.

5.2. Determinants of the Efficiency

To determine the sources of variations in TE, the study estimates the relationship between TE and some environmental variables. We have explained the bootstrap procedure in section 3. The model is written as:

$$\hat{\theta}_{it} = \beta_0 + \beta_1 DC_{it} + \beta_1 DH_{it} + \beta_1 EA_{it} + \beta_1 EI_{it} + \beta_1 EE_{it} + \beta_1 RE_{it} + \beta_1 RA_{it} + \beta_1 AG_{it} + \beta_1 BR_{it} + \beta_1 AT_{it} + \varepsilon_{it} \quad (3)$$

where $\hat{\theta}_{it}$ is the biased corrected efficiency score. The environmental variables notations are described in table 1.

Table 5 shows the results of the truncated regression. The dummy for conventional banks (DC) and the dummy for Hybrid banks (DH) are significant and positive. This also implies a significant difference in the efficiencies of the three groups of banks presented in Table 4 and Figure 1.

Table 5: Truncated Regression

Variables	Coefficients	Standard Error
DC	0.039**	0.019
DH	0.041**	0.018
EA	-0.007	0.043
EI	-0.021	0.016
EE	0.000***	0.000
RE	0.009	0.029
RA	-0.559	0.467
AG	-0.001**	0.001
BR	0.000***	0.000
AT	0.000***	0.000
Constant	0.843	0.042

***, **, and * indicate significance at 1%, 5%, and 10% level of significance.

Earning assets to total assets (EA), total expenses to total income (EI), Return on assets (RA), and return on equity (RE) are found to be insignificant. Bank age (AG) is significant and has a negative coefficient, indicating bank age has a negative effect on efficiency, although the impact is very small. The impact of many branches (NB) and the number of ATMs (AT) is significant and positive but its magnitude is almost near zero.

6. CONCLUDING REMARKS

The number of Islamic banks has grown over the sample period and more conventional banks are offering Islamic banking products. The technical efficiency analysis by applying the double bootstrap approach has enabled us to estimate the bias-corrected efficiency score. We can conclude that hybrid banks are performing better than their other counterparts in recent years. The reason can be the trust of people in already established banks. It’s always hard to make a reputation in any business.

Islamic banks have shown a steady increase in capturing their share in the banking industry of Pakistan from 2003 to 2010. Islamic banks are almost at par with conventional banks in terms of technical efficiency. In the financial crisis period of 2008-2009, all banks suffered almost the same in terms of technical efficiency. We do not have evidence that Islamic banks were better performing in terms of technical efficiency in a crisis period, we can say hybrid banks were also a bit better off in that period too.

The environmental variable regression reveals that there is a significant difference in the technical efficiencies of the three groups of banks, and it’s not by chance. Moreover, the number of branches and number of ATMs have a significant effect, but very small in magnitude. Interestingly bank age is having a negative impact on bank efficiency, although the magnitude here is also very small.

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Contemporary Non-Tariff Measures Under the WTO Regime: Case of Pakistan Export to European Countries

ABSTRACT

The World Trade Organisation (WTO) initiated a uniform set of non-tariff measures in 1995, which are now considered as emerging barriers in world trade patterns. The non-tariff measures impede the export of WTO member states. The WTO has asked its members to limit tariff rates. Hence, members have left with only option to levy non-tariff barriers to transform exports. This article's main objective is to examine the effects of non-tariff measures on export of Pakistan to European countries from 1995 to 2018. Poisson Pseudo Maximum Likelihood (PPML) and Zero-inflated PPML (ZI-PPML) estimation methods are deployed to address zero-export in many years and over-dispersion data of export to specified countries, based on the gravity model. The findings show that the GDP of Pakistan and European nations, tariff, distance, and Non-tariff Measures (NTMs) are core determinants, while in some cases, NTMs initiated are export restrictive. In this perspective, tariff, and non-tariff measures are utilized to administer Pakistan's export to the subject region. Similar to the developed countries, Pakistan should also address non-tariff barriers effectively for favourable trade flows.

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Author's contribution in the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

World Trade Organisation (WTO), since its inception in 1995, has promulgated various multilateral agreements to implement for its member states. These agreements include various non-tariff measures Agreements on Sanitary and Phytosanitary (SPS)[1] and Technical Barriers to Trade (TBT)[2] (non-tariff measures-NTMs) have been considered the most effective for enforcing technical and quality standards in the WTO era. The main spirit of NTMs was to save the WTO from trade distortions, which is the core notion in the neoclassical economies. The NTMs have changed such notions by targeting improved economic access and competition in international trade, and reducing domestic subsidies. This would attain through fewer tariffs of quantitative restriction, existing tariffs, quality standards, and technical standards' enforcements. One of the most important presumptions in the neoclassical theories was that their compact information related to the market and the elimination of subsidies and tariffs, which would lead to an increase in NTMs. In a unique way, Pakistan addressed such NTMs, with potential huge growth, higher industrialization, and export to European countries.

The economy of Pakistan is characterized by incomplete information that leads to distorting and trade preventive. Such aspects are indispensable in foreign trade in multiple merchandise. The commodities are not homogenous in multilateral trade with Europe. Countries and firms follow various quality and technical standards and safety regulations to regulate exports. Importing countries sometimes can't ascertain the quality and standards of commodities merely by examining the products at port or during the pre-shipment inspection. Both SPS and TBT handle such issues under the WTO regime.

Consumers and producers have the potential to sell and purchase products of various qualities at the given prices. Henson and Traill (1993) and Viscusi et al. (1995) reported that officials don't intervene in such capitalist settlements. Darby and Karni (1973), Nelson (1970), and Nelson (1974) deliberated it as a distinction of various commodities into three clusters, experience goods, search goods, and credence goods. For the search goods, buyers may ascertain a commodity's quality before its purchase by checking them during pre-shipment physical examination of tea is sufficient to ascertain its character before its export.

The neoclassical verdict may hold the goods in similar cases. The second experiences good, where the purchaser may ascertain the quality of good till, he buys and use it properly. If the commodities are bought repeatedly, where the selection choice is based on previous experience, market forces may take care of themselves. If the buyers buy commodities repeatedly, a company that sells high-quality goods may charge even higher prices. In a case, market imperfections can be managed by repeat purchases (e.g., meat) and firms' goodwill. Third segregation includes credence good where consumer information is imperfect pre-purchase and post-purchase. Chronic and adulteration impact low-level exposures to residues of toxins and pesticides can be risky and unhealthy for the health of humans in the short or long term or due to repeated use. SPS and TBT cover these chronic adulterations. In similar cases, external regulatory parameters are needed in edible trading commodities where standards and quality are of great concern. WTO has asked member states to initiate and implement SPS and TBT that address harmonizing technical and quality standards and restrain discrimination in multilateral trade.

The objective of the research article is to analyse the effects of SPS and TBT (initiated by the Europe countries) against the export of Pakistan to selected European countries. The study also aims to analyse the requisite policy recommendations to address international quality and technical standards to boost exports of Pakistan to European countries.

[1] In international trade, quality and standards set by the WTO to save living human, plants and animal

[2] Technical standards in international trade set by the WTO

This research article is managed in the following scheme: the first section introduces the NTMs, and the second section presents SPS and TBT related to the literature review to bring the significance and research gap. Section 3 provides methodology and data issues, and section 4 presents results with a discussion. The last section brings conclusions and policy recommendations for more export to Europe in the presence of NTMs.

2. TBT AND SPS AGREEMENTS AND IMPLICATIONS

SPS and TBT did not receive much response so far from the industry in Pakistan, a kind of misperception in understanding the gap between SPS and TBT during the WTO regime. This distinction between Non-Tariff Barriers (NTBs) is of complex and technical nature, especially at the goods level. The SPS covers the food and agriculture sector, while TBT addresses all commodities, including food and food-related goods. SPS targets protection for animals, plants, human lives, and health against diseases and pests from the export of food and agri-products. In contrast, TBT deals with trading commodities, including shapes, packaging material, weight requirements, labelling issues, and technical safety.

Articles 3.1 and 3.2 of SPS state, "Members shall base their sanitary and phytosanitary measures on international standards, guidelines, and recommendations. The sanitary and phytosanitary measures that conform to the international standards, guidelines, and recommendations will be deemed necessary to protect human, animal, or plant life or health." International technical standards and safety guidelines and suggestions are presented by the Codex Alimentarius Commission of the World Health Organisation (WHO) and Food and Agriculture Organisation (FAO), and the International Standards Organisation (ISO). Alimentarius guidelines have no backing of international laws, whereas WTO supports quality and technical standards via agreements of SPS and TBT, which declares these technical and quality standards de fecto mandatory for members.

TBT limits the members of WTO to initiate technical and safety laws, conformity assessments, and procedures. Contrariwise, TBT didn't permit expediting extra redundant barriers to export goods, rather TBT should be strong technically and justifiable based on evidence and scientific information. Article 1.3 explains that all goods would be subject to regulations of WTO's agreement on TBT (GATT, 1994). This TBT agreement's Article 2 highlights that members would confirm technical safety standards. The quality standards would not expedite extreme measures for trade flows among WTO members. Resultantly, the technical safety measures bylaws issues would not be trade-restrictive but rather abide by legitimate explicit targets. National Enquiry Points for SPS and TBT are cited in Annex 1, and they deal with all issues related to quality and technical standards.

United Nations Conference on Trade and Development (UNCTAD, 2019) has segregated non-tariff measures into two core sections, technical and nontechnical measures for exports. In the case of exports, technical and safety measures include SPS, TBT, pre-shipment inspection, and other requirements. Nontechnical measures for exports include non-automatic import licensing, quotas, contingent export protective measures, and restrictions that don't include SPS and TBT – taxes and charges, competition, investment measures, and subsidies. Exports comprised export-related measures (UNCTAD, 2019).

3. EMPIRICAL LITERATURE ON TBT AND SPS

3.1 Theoretical Background

NTMs are classified into three categories: 1) levied on imports, including import quota, custom procedure, and administration fee, imports licensing, and prohibition; 2) imposed on export, including export quota, export prohibition, subsidy, voluntary export restraint, and export tax; and 3) levied in the domestic markets

(Staiger, 2012). Anderson & Wincoop (2003) and Anderson & Wincoop (2004) added to the literature by incorporating multilateral resistance trade cost and firm heterogeneous behaviour in the gravity model.

Melitz (2003), and Bernard et al. (2003) examined firm heterogeneity and reported that not all the firms in a country import goods, whereas a few countries join the foreign trade over a certain time. The motivation is fixed cost that is market specific and quite greater in import against the domestic trade. Subsequently, the import data will have zero entries. Standard gravity literature disregards the prevalence of zero imports, whereas Helpman et al. (2008), Melitz & Ottaviano (2008) and Chen & Novy (2011) introduced gravity model with the theoretical interpretation. Metlitz (2003) presented the trade model with the firms' heterogeneity.

Poisson Pseudo Maximum Likelihood (PPML) model is vulnerable because of over-dispersion in the explained variable (Burger, et al. 2009), and larger the number of zero in it, which leads to the consistent but inefficient estimates. Silva and Tenreyro (2011) reported that PPML brings consistent coefficients despite over-dispersion in the explained variable (with a prerequisite of conditional variance not equal to conditional mean); a larger number of zeros doesn't affect its existence. Head and Mayer (2014) claimed Multinomial Pseudo Maximum Likelihood (MPML) works in the simulation than the PPML. Prehn and Brummer (2012) studied PPML efficiently in the presence of over dispersion and found that PPML was well behaved in the bimodally distributed dataset.

3.2 Empirical Literature on Non-tariff Measures

Alaeibakhsh and Ardakani (2012) who quantified the trade impacts of quality and technical regulations on export and reported the negative impacts in the case of Europe Union members. But Xiaohua and Qiu (2012) reported that TBT affects countries' economic growth. A developed country's TBT notification decreases the probability of exporting by the developing countries; however, it increases their export volume. They also ascertained that TBT affects the export of developing countries but impacts the export of developed countries insignificantly, while Essaji (2008) reported similar opinions about the quality and technical regulations initiated by the developing and developed countries. Earlier, Bao and Qiu (2010) found that China has compromised its imports by initiating TBT.

Disdier (2008) described that the NTBs impact developed countries and small firms are damaged at a larger scale. Staiger (2012) complied with Disdier (2008) and reported that during the WTO administration, the world had faced the SPS and TBT measures since 1995 against the agro-products, and these NTBs are trade restrictive than the tariff levels. Arita et al. (2015) has conducted a quantitative analysis of some of the selected TBT and SPS affecting the E.U. and USA agro-trade. They used a gravity model and estimated tariff equivalent NTMs impact on E.U. and USA. The NTMs were assessed as barriers to mutual trade, and the ad-valorem tariff equivalents of these NTMs were examined to be greater than the current tariff rates and tariff rate quota.

Karki (2002) studied TBT and SPS in the SAARC perspective and found that lack of harmonization in quality standards, inadequate regional capacity, compliance cost, SMEs, inadequate testing, certification and accreditation, and legal consistency are major issues in addressing compliance issues. The region needs to review and harmonist regulations to enhance regional trade compliance with NTBs. Information sharing and legal competency may also bring voluminous trade. Khan and Haider (2003) reported that WTO Agreements on TBT and SPS are formulated to harmonize quality and standards to facilitate technical assistance for developing countries.

The above theoretical and empirical literature signified the need for a study between developed European countries and Pakistan. The number of NTMs is increasing under WTO, but the capacity of Pakistan to address them with equal scope needs technical capacity.

4. DATA AND METHODOLOGY

In this research, the secondary data set of used export data of Pakistan to European countries is collected from United Nations Commodity Trade Statistics dataset. GDP data is collected from World Bank, data on distance from Institute for Research on the Int'l Economy, tariff from World Bank, and SPS and TBT from WTO. Table 1 forwards data with its description of these variables.

Table 1: Variables description and sources

Variable	Description	Proxy	Data source
Export(EXPpt)	Export value (dependent variable)		UNComtrade
TBT (tbt)	Natural logarithm of Technical Barrier to Trade	Measure of restrictiveness	WTO
SPS (sps)	Natural logarithm of sanitary and phytosanitary	Measure of restrictiveness	WTO
GDPp (gdppt)	Natural log of Pakistan GDP current U.S. dollars as a reporter country	Size of economy & demand side effect	WDI
GDPeu (gdpeut)	Natural log of Partner countries' GDP current U.S. dollars	Trading capacity	WDI
Exchange rate (exrat)	Official exchange rate (Local Currency Unit LCU per US$ period average)	Competitiveness	World Bank
Tariff rate (tarr)	Effectively Applied Weighted Average %	Measure of restrictiveness	World Bank
Distance (dista)	Natural log of distance in km between capitals of Pakistan and European country's capital cities	Transportation and logistics cost	CEPII
Contiguity (con)	Dummy equal to unity if two countries share a common border	Information cost	CEPII

Gravity Model Approach

The gravity model approach is used to quantify the impacts of SPS and TBT on Pakistan's exports during the WTO regime, i.e., 1995 to 2020. This is one of the standard approaches to the gravity model's estimation; this analysis would add to gravity literature with the core application of SPS and TBT datasets. The gravity model examines export and the impacts of safety and technical regulations. This model was introduced by Tinbergen (1962) and Linnemann (1966) to analyse trade without biased export impediments. The model is developed in log formation (equation 1), and the gravity model for export is derived as follows:

$$ln(eXP_{pt}) = \tau_0 + \tau_1(tarr_{pt}) + \tau_2 ln(tbt_{pt}) + \tau_3 ln(sps_{pt}) + \tau_4 ln(gdp_{pt}) + \tau_5 ln(gdp_{eut}) + \tau_6 ln(dista_{peu}) + \tau_7(exrat_{pt}) + \mu_{ijt} \quad (1)$$

SPSpt and TBTpt show the number of SPS and TBT cases initiated by selected European countries against exports of Pakistan, and distance is the gravity variable between Pakistan and European countries. PPML and ZI-PPML (Zero-inflated PPML) are deployed to estimate the model, and the methods deal with many zero in the exports dataset. It also permits the identification of challenges of time-invariant factors (distance). By using the poisson estimator for fixed effects (unlike PPML), time-invariant regressors would not be skipped, but different pairs of never trading partners from the sample (Silva & Tenreyro, 2006; Silva & Tenreyro, 2011; Kareem et al., 2016). Skewness, Kurtosis, Shapiro-Francia W', and Shapiro-Wilk W normality tests proved the non-normality of data necessary for PPML and ZI-PPML.

5. EMPIRICAL RESULTS AND DISCUSSION

Descriptive statistics of gravity model variables comprised mean, standard deviation, minimum and maximum values. The total number of export values is 648, whereas 232 (36%) export values are missing, indicating that Pakistan didn't export during all years from 1995 to 2018. ZI-PPML method includes all export data and bilateral zero export values and omits inconsistent estimates conceived from the log-linear approach (Silva & Tenreyro, 2006). ZI-PPML estimates transform the gravity model of equation 2 to the following exponent format:

$$Poisson: E(y \mid x) = E(EXP_{pt} \mid x) = exp(x'\tau)$$
$$= exp\big(\tau_0 + \tau_1 tarr_{pt} + \tau_2 tbt_{pt} + \tau_3 sp_{ijt} + \tau_4 gdp_{pt} + \tau_5 gdp_{eut} + \tau_6 dista_{peu} + \tau_7 exrat_{pt}\big) + \mu_{ijt} \quad (2)$$

Where $E(y \mid x)$ is expected values and the mean of dependent variable y (export from Pakistan to EU EXpt) conditional on its independent variables x are estimates coefficients. E.U.'s SPS and TBT cases come into force between certain periods (years) when it is initiated. Database of WTO comprises SPS and TBT measures initiated. SPS and TBT cases data is deployed and expedited by respective E.U. against Pakistan.

Data description

In this part, the descriptive statistics of the dataset are forwarded in Table 2. Comparing the export data with the rest of the variables observed that 232 values of exports are missing, which brings that Pakistan doesn't export either to all E.U. countries or in all the years during the analysis period. The figure below confirms that the data is not normal, which is a precondition to applying the maximum likelihood estimation process via PPML and ZI-PPML.

Table 2: Descriptive Statistics of Variables

Variables	Obs.	Mean	Std. Dev.	Min	Max
Export	648	0.138447	.2905758	0	1.728637
Lntariff	648	0.206248	.6660288	0	3.251671
Lnlcu	648	4.214882	.3619693	3.454507	4.802578
lngdpp	648	4.876277	.5839536	4.104889	5.744829
lngdpeu	648	5.050369	1.716265	1.235452	8.29324
Lnsps	648	1.192264	1.30325	0	4.158883
Lntbt	648	2.40856	2.017452	0	6.436151
Lndista	648	1.620993	.1497922	1.289907	1.967468

Cases of SPS and TBT of respective European Union countries came into force when it was initiated. WTO dataset of ITIP gives the data of initiated SPS and TBT cases. The SPS and TBT cases were initiated and enforced by the governments of respective countries against Pakistan.

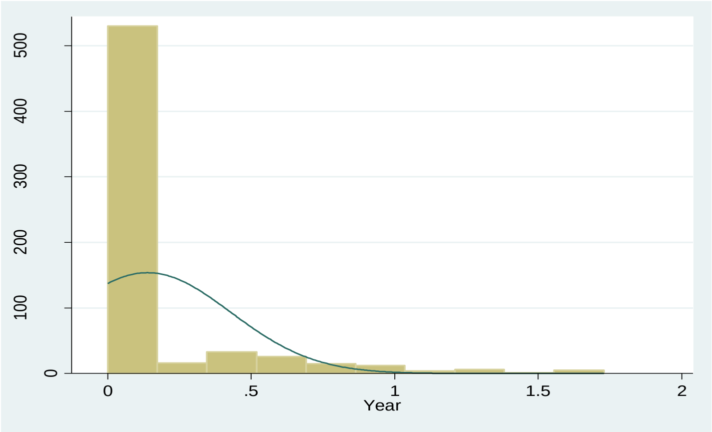

Figure 1: Data distribution of export value (US$)

Data source: UNComtrade, 2021

Sapiro-Francia W and Shapiro-Wilk W tests are applied (Table 3). Figure 1 and all the tests confirmed that export data is not normally distributed. This non-normality export data distribution is a prerequisite for deploying PPML and ZI-PPML.

Table 3: Non-normality distribution tests

Shapiro-Wilk W test of normal data					
Variable	Obs.	W	V	z	Prob > z
Import	648	0.61977	161.674	12.366	0.000
Shapiro-Francia W' test of normal data					
Variable	Obs.	W'	V'	Z	Prob > z
Import	648	0.63334	166.547	11.409	0.0001

Estimated results of ZI-PPML with gravity model (and robust standard errors) are shown in Table 4. The European Union countries initiated SPS and TBT to examine and administer quality and technical parameters for Pakistan. Against the WTO rules and regulations, SPS and TBT are proxies for trade restrictiveness. The results of ZI-PPML witness that Pakistan's exports decline around 0.73 percent after a 1 percent increase in tariff rate. A tariff is a historical restriction for export to any country. Europe, as a protectionist region, has blocked exports from Pakistan. It proved very effective as the value of the coefficient is very high. Fassarella, et al. (2011), Dong & Zhu (2015), Mustafa, et al. (2020), and Olper & Raimondi (2002) implemented various methods, including PPML having similar results. The TBT is a non-tariff barrier to restrict exports, which is initiated to help increase the exports of Pakistan or to improve the technical standards of export commodities for the consumer protection of the European Union. The coefficient of TBT shows that a 1% increase in TBT will increase the exports by 0.26%. It complies with previous research which TBT is promoting to increase exports. It also describes that Pakistan was capable of complying with TBT technical standards posed via WTO. The results assist the previous research of Bao and Qiu (2010).

Table 4: Coefficient Estimation Results of Gravity Model with PPML ZI-PPML

Variables	PPML coefficient	(P-value)	ZI-PPML coefficient	(P-value)
Tariff	-0.6279	(0.35)	-0.7324*	(0.00)
TBT	0.3093*	(0.00)	0.260*	(0.00)
SPS	-0.1532*	(0.00)	-0.1302*	(0.00)
GDPp	2.3552	(0.44)	2.9052*	(0.00)
GDPeu	0.9851	(0.43)	0.9279*	(0.00)
Distance	-4.766*	(0.00)	-3.047*	(0.00)
Exchange Rate	-2.976	(0.69)	-4.187*	(0.00)
No. of observation	648		648	
No. of groups	27		-	
Inflate Equation Results				
Exchange Rate	-		-4.4805	(0.00)*
SPS	-		5.4168	(0.00)*
TBT	-		-0.2435	(0.00)*
Distance	-		-3.5763	(0.15)
Inflation model (logit)	Wald chi2(7) = 2124.88			
Log Pseudolikelihood	-171.7074 Prob > chi2 = 0.0000			

Note: * witnesses significance at $\alpha = 1\%$

The coefficient of SPS depicts that a 1% decrease in SPS will increase the exports by 0.13%. It confirms with several types of research that SPS is trade restrictive to limit the exports of Pakistan. It also elaborates that Pakistan could not comply with the SPS quality and standards. This result helped the previous research by Thuong (2018), Peterson et al. (2013), Kareem et al. (2016), and Schlueter et al. (2009); these studies produced similar results. The estimated result showed that an increase of 1% in Pakistan's GDP leads to an increase in Pakistan's exports by 2.91%. The result is in line with many researchers, including (Kareem et al., 2016; Thuong, 2018; Hermawan, 2019). These studies are recent in the available literature. Similarly, an increase in GDP of partner European by 1% enhanced exports by 0.93%, assuming the ceteris paribus. European counties' GDP is assumed as a proxy of trading capacity. The results were similar to many types of research inducing (Kaur & Parmjit, 2011; Ronen, 2017; Chen et al., 2018).

Regarding the logistics and transportation costs variables, ZI-PPML estimates revealed that distance affected the probability of Pakistan's exports. It was worth noting that the bilateral distance enhanced the likelihood of zeros. The distance between Pakistan and its European trading partners increased by 1%, and the exports increased by 3.05%. The exchange rate is a proxy of the competitiveness of Pakistan's exports with the rest of the world; it has witnessed a negative sign; an increase of 1% in the exchange rate decreased export of Pakistan by 4.19%. The exchange rate is essential for Pakistan to determine its export.

6. CONCLUSION

The main objective of the research was to analyse the impact of SPS and TBT on exports of Pakistan to the selected European countries under the WTO regime. European countries initiated many SPS and TBT measures for managing multilateral trade from 1995 to 2018. The empirical results of the regression estimation are found in European countries during the analysis period. Hence there is much scope for increasing exports through advancements in NTBs. The estimation shows that increasing the tariff rate has decreased Pakistan's exports. This also deducted that SPS is more effective than TBT in restricting Pakistan's exports. An increase in GDPs of Pakistan and European countries has been proved export promoting in case of Pakistan. Pakistan needs to improve quality standards in the case of SPS as it is creating hurdles in exports, where TBT is trade promoting either due to low tech few exports or country has come up with requisite international technical standards. Pakistan may seek help from European countries (historical trade partners) to enhance its capacity to keep export quality abreast.

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Modeling Volatility Spillover and Role of Volatility Spillover Effect to Improve Forecasting Performance of GARCH Models Based on Varying Distributions

ABSTRACT

The presented study endeavor to examine whether financial returns' volatility spillover effect imparts a role to improve the forecasting accuracy of GARCH family models based on various error distributions. An empirical investigation is conducted by employing standard GARCH, EGARCH, and GJR-GARCH models. Three error distributions, normal, Student t, and General Error Distribution are used in the analysis. Daily data spanning from August 4, 1997, to April 28, 2022, has been analyzed. The strength of the study lies in utilizing the volatility spillover effect along with none normal error distributions to improve the forecasting accuracy of three GARCH family models for stock and currency markets' returns, in the context of Pakistan. In-sample estimation results from all three models validate the existence of significant volatility spillover among the stock and currency markets of Pakistan. Whereas, out-sample forecasting results provide evidence regarding accuracy gain from the perspective of stock and currency markets' returns forecasting. Along with the volatility spillover effect, EGARCH and GJR-GARCH models based on Students t and GED distributions provide better forecasts for stock market and currency market returns. The results of the study hold promise for practical significance for asset allocation and financial risk management applications.

Keywords
Financial Markets, Volatility Spillover, Forecasting, GARCH-type Models, Non-Normal Error Distributions

JEL Classification
C53, D53, F31

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1. INTRODUCTION

Modeling and forecasting financial markets' returns and their volatility has remained a matter of much attention since the seminal evolution of Autoregressive Conditional Heteroscedasticity (ARCH) family models by Engle (1982); Bollerslev (1986); Nelson (1991) etc. The family of ARCH models was mainly designed to deal with the heteroscedastic nature of financial time series. However, one major drawback embedded in ARCH family models is their assumption of the normally distributed error term. Pragmatic studies on financial econometrics advocate that financial time series often exhibit the feature of leptokurtosis (Baillie & Bollerslev, 2002; Ho et al., 2013). The use of conventional ARCH family models that are based on the normality assumption of error term may lead to underestimation or overestimation of the second moment of financial time series i.e. conditional volatility (Charfi & Mselmi, 2022). To overcome these consequences, clearly identifying appropriate innovation distribution is a matter of the day for accurate estimation and forecasting of financial time series.

Over time, cross markets linkages from the perspective of information flow mainly in terms of volatility spillover render significant implications for investors and policymakers (Ross, 1989). Hence, utilizing this information flow in forecasting financial markets returns will be of paramount significance in managing portfolio diversification, option pricing, and devising hedging strategies (Chang et al., 2018). Since exchange rates and stock prices are key determinants of portfolio risk, therefore cross-market volatility spillover may help investors and policymakers to predict financial markets behavior with greater precision (Mishra et al., 2022). This study does indeed behold such an expectation.

Enriched and efficient analysis always requires a complete and clarified description of the conditional distribution to which the data-generating process belongs (Baillie & Bollersley, 1992). This conclusion has been arrived at by analyzing exchange rate returns through the GARCH model based on non-normal error distribution. Therefore, a good way to extract the benefit from cross-market information is to utilize it in GARCH family models based on varying error distributions. Keeping these things in mind the present study attempts to answer the research question, of do volatility spillover across financial markets, helps to improve the forecasting accuracy of GARCH family models. Another research question analyzed in this study is whether none normal error distributions impart to forecasting gain in GARCH family models. Two none normal error distributions, Students t and General Error Distribution (GED) are used in three GARCH family models. Among financial markets, the Pakistan Stock Exchange (PSX) 100 index and bilateral nominal exchange rate, Pak-rupees in terms of US-Dollar have been selected for analysis. High-frequency daily data spanning from August 4, 1997, to April 28, 2022, has been analyzed by using three financial econometric models; standard GARCH, EGARCH, and GJR-GARCH model. This study holds novelty in terms of utilizing the information on volatility spillover to determine the predictability gain for GARCH family models along with some varying distributions. The results' implications of the study hold paramount importance for investors, policymakers, and researchers. Investors will get help in terms of managing their investment portfolio. Policymakers will be benefited from the perspective of setting financial policies and keeping an eye on the future behavior of financial markets.

The rest of the study constitutes four sections. A literature review is discussed in section 2. Section 3 covers methodology and data. Results and their discussion is provided in section 4 and section 5 concluded the analysis of the study.

2. LITERATURE REVIEW

Substantial evidence of systematic volatility plays an imperative role in volatility spillover across financial markets. A renowned study by Kanas (2000) has reported that significant volatility spillover may induce the nonsystematic risk that reduces gains from portfolio diversification. The first potential theoretical underpinnings regarding interactions among stock prices and the exchange rate are provided by Dornbusch and Fischer (1980) in the name of the flow-oriented model. According to this model exchange rate exert a positive significant impact on stock prices. Whereas, in the stock-oriented model, Branson (1983) demonstrated that stock prices affect the exchange rate in a significant and positive direction. These theoretical explanations establish the existence of some interlinkages between stock markets and currency markets. Owing to these cross markets' interlinkages, any change in returns' volatility of the stock market (currency market) delivers volatility in currency markets (stock market) returns as well.

In literature, an easy and common conventional way adopted to improve the forecasting performance of the GARCH family model is to use the non-normal error distributions. This modification makes the GARCH model more flexible to capture and model a thicker tail, higher kurtosis, and skewness of returns data. Non-normal error distributions have been used in both symmetric and asymmetric GARCH models. Bollerslev (1987) and Hamilton and Susmel (1994) employed Normal, Student t, and GED distributions respectively. Estimation and forecasting results of both studies show that Student's t innovations should be considered because Student's t distribution better captures the leptokurtic behavior of financial returns. Zhang (2009) and Shamiri and Isa (2009) analyzed symmetric and asymmetric GARCH, EGARCH, and NAGARCH models based on Students t, Normal, skewed Students t, Normal Inverse Gaussian and Generalized Error Distribution (GED) for the German stock market and of Malaysian stock market respectively. It has been reported that accurate volatility forecasts depend on the choice of error distribution rather than the type of GARCH model. Analysis suggests that the GARCH model based on heavy-tailed error distributions provides better volatility estimates and volatility forecasts.

Volatility forecasting of the Standard and Poor's 100 stock index data series has been done by Liu and Hung (2010). Analysis has been carried out using six types of symmetric and asymmetric GARCH models based on standard Normal, Student t, and skewed generalized t distributions. Empirical results of the analysis revealed that the asymmetric GARCH model produces better volatility forecasting with non-normal error distributions. The role of Student t and GED distribution to improve the forecasting accuracy of the GARCH model has been explored by Vee et al. (2011). It has been demonstrated in the results that the GARCH model based on GED distribution better performs to improve the forecasting accuracy. The same results have been reported by Kumar and Patil (2016).

Kosapattarapim et al. (2012) evaluated the performance of GARCH models based on six error distributions for Thailand, Malaysia, and Singapore stock markets. Results of the study suggest that non-Normal error distributions contribute significantly to improving return volatility forecasts. While analyzing Nigerian stock market volatility, Adepoju et al. (2013) and Atoi (2014) argued that the GARCH model based on Student t distribution is best for volatility estimation and forecasting. Because, to cope with risk, volatility prediction using Student t distribution will help to reduce the likelihood of extreme losses by market players in the stock market. The same results have been reported by Aftab et al. (2019). Using symmetric and asymmetric GARCH models based on Normal, Students t, and GED distribution, Mubarik and Javid (2016) estimated and forecasted the volatility of PSE-100 index returns. It has been reported that asymmetric GARCH models based on Student t distribution perform better in terms of forecasting PSX-100 index returns.

Ahmed and Naher (2021) forecasted exchange rate volatility for Bangladesh. GARCH, EGARCH, APARCH, TGARCH and IGARCH models based on Normal and Student t distribution have been analyzed. Results of the study revealed that the GARCH model with Students t distribution performed best on the perspective of out-of-sample exchange rate volatility forecast. Charfi and Mselmi (2022) used GARCH and EGARCH models based on Normal, Students t and Normal Tempered Stable distribution to forecast exchange rate volatility. It has been demonstrated that GARCH and EGARCH models with Normal Tempered Stable distribution outperform on the perspective of out-sample forecasting, relative to other distributions.

Enough literature has been evidenced on the role of none Normal error distributions to improve GARCH model forecasting. However, a little strand of studies has been evidenced in investigating the role of cross markets volatility spillover on the forecasting performance of GARCH-type models. From this perspective, Phan et al. (2016) explored the effect of volatility spillover on the predictability gain of crude oil and stock market volatility of three developed countries. The EGARCH model has been applied to high-frequency data. Results of both in-sample and out-sample analysis demonstrated that cross-market volatility spillover improves price volatility prediction of crude oil and the stock market. The effect of volatility spillover from other assets and stock exchange on forecasting accuracy of oil price volatility has been analyzed by Degiannakis and Filis (2017). Results of the Heteroscedastic Autoregressive (HAR) model suggest that using volatility spillover, as an information channel, plays a significant role in improving forecast accuracy of oil prices realized volatility.

Mubarak and Javid (2017) estimated and forecasted high and low-beta portfolio stock returns' volatility of the PSX-100 index. Analysis has been carried out using a general-to-specific approach in the EGARCH-M model. Results of the study reported that low beta portfolio stock returns' volatility provided better in-sample and out-sample forecast ability. The impact of the volatility spillover effect, from the U.S. stock market, on forecasting the accuracy of other international stock markets' returns has been investigated by Liang et al. (2022). In-sample estimation and out-sample forecasting have been conducted by using the GARCH model. It has been demonstrated in the results that the realization of information on the spillover effect from the U.S.A. credibly improves the forecasting accuracy of other markets' stock prices and their returns. The predictability role of gold and exchange rate volatility in forecasting stock returns' volatility of the Hang Seng Index (HSI) has been investigated by Dai et al. (2020). Results of the AR model suggest that exchange rate volatility imparts significant predictability gain for in-sample and out-sample stock return volatility forecasting.

Chatziantoniou et al. (2021) investigated the predictability usage of volatility spillover from uncertainty indices and the US stock exchange market to oil price volatility prediction. The results of the HAR model advocate that information on volatility spillover does not impart significant predictability gain in oil price volatility. The authors discussed that this result may arise due to the analysis of low-frequency data. To check this assertion, using high-frequency data, Wu et al. (2022) investigated the role of information on volatility spillover in improving oil price volatility forecasting. Results of the study recommend that volatility spillover has significant predictability power in volatility forecasting and can be used in the forecasting field. Ghani et al. (2022) utilized the information on economic variables and uncertainty index to improve the forecasting accuracy of Pakistan stock market volatility. Forecasting results of the GARCH model suggest that using the information on economic variables including exchange rate valuably contributes to the forecasting accuracy of PSX.

A review of historical literature evidenced that a huge volume of studies has been conducted to improve the forecasting performance of GARCH family models. Some studies attempted to do so using non-normal error distributions in GARCH models. Whereas, few other studies used information on economic variables and information on volatility spillover for this purpose. Yet literature encompasses a gap in neglecting the role of information on volatility spillover together with non-normal error distributions to improve the forecasting performance of GARCH models. The intended study has made an effort to address this loophole in existing literature using three econometric models.

3. METHODOLOGY

The main objective of this study is to investigate the role of volatility spillover in financial market returns forecasting using GARCH family models. To meet this endeavor, one way is to split the full sample data into two groups. The first group of data is known as an in-sample data set and the second group of data is known as out-sample data set. The in-sample data set is used for estimating the parameter of the model. Whereas, the out-sample data set is used for returns forecasting.

Financial markets (stock market and currency market) return R_t^x has been calculated as;

$$R_t^x = lnP_t - lnP_{t-1} \tag{1}$$

Whereas, financial markets' returns' volatility has been generated from GARCH/EGARCH/GJR-GARCH models.

3.1. GARCH Model

For the sake of forecasting, GARCH family models are used when there is an ARCH effect in the data. The standard GARCH model developed by Bollerslev (1986) is based on the assumption of symmetric effect[1]. This is due to the reason that the error term in the variance equation of the GARCH model has been taken in square form. GARCH models are based on the concatenation of two main equations; mean equation and variance equation. An important feature of the GARCH model is that variance of the error term in the mean equation is modeled as a linear function of past squared errors and previous conditional variances. Following Enders (2015), the corresponding mean and variance equations used for estimating the volatility spillover through the Standard symmetric ARMA(p, q)-GARCH(p, q) model are as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{2}$$
$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \pi 1_y h_t^y \tag{3}$$

In equation (2) R_t^x is representing returns of variable x at time t. Where x represents stock market returns and currency market returns. R_{t-i}^x is the preceding period returns of variable x. Suitable structure and order of mean equation (2) are determined with the help of Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF). In equation (3) h_t^y is returns' volatility of variable y and $\pi 1_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns' volatility (RPSX) to exchange rate returns' volatility (REXR).

3.2. GJR-GARCH Model

Symmetric models like ARCH and GARCH models are based on the assumption that positive and negative shocks have a symmetric effect on volatility. Because error terms have been taken in a square form in the model. However, generally, this assumption is frequently violated in practice. It is often observed as well as reported in the literature that bad news has more impact on volatility relative to good news. This phenomenon is called the leverage effect introduced by Black (1976). To capture the leverage effect, Glosten et al. (1993) introduced the GJR-GARCH model. This model uses a dummy variable to capture the leverage effect.

ARMA (p, q)-GJR-GARCH (p, q) model employed in this study is as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{4}$$
$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \gamma \varepsilon_{t-1}^2 I_t + \pi 2_y h_t^y \tag{5}$$

In equation (5) I_t represent dummy variable, which is equal to one if the preceding period error term is negative and zero otherwise. h_t^y is returns' volatility of variable y and $\pi 2_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns' volatility (RPSX) to exchange rate returns' volatility (REXR). The remaining explanation is same as in equation (3).

[1] Effect of good and bad news is different.

3.3. EGARCH Model

In the GJR-GARCH model leverage effect is assumed to be quadratic. The EGARCH model introduced by Nelson (1991) also captures the leverage effect. Where the leverage effect is taken as exponential. Like the standard GARCH model, the GJR-GARCH model imposes non-negativity constraints on estimated parameters. Whereas, in the EGARCH model variance equation is in log form hence negative co-efficient is permissible. Another advantage of the EGARCH model over the GARCH and GJR-GARCH models is that it allows a more natural interpretation of shock persistence letting standardized errors.

The formal, ARMA (p, q)-EGARCH (p, q) model is as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{6}$$

$$log(h_t) = \omega_0 + \sum_{i=1}^{p} \gamma_j \, log h_{t-j} + \sum_{j=1}^{q} \rho_j \left| \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{m=1}^{r} \theta_m \frac{\mu_{t-m}}{\sqrt{h_{t-m}}} + \pi 3_y log\left(h_t^y\right) \tag{7}$$

In equation (7) $log(h_t)$ represents the log of variance of the error term in equation (6) which mechanically constrains the variance to be positive. ω_0 represent the constant level of volatility. The logarithm of the conditional variance (h_{t-j}) indicates that the leverage effect is exponential, rather than quadratic. The coefficient ρ_j captures the reaction of volatility in response to changes in the news. Residual modulus measures the response to positive news. θ_m captures the response of volatility to both positive and negative news, as modulus is not being taken here. $\pi 3_y log\left(h_t^y\right)$ is the returns' volatility of variable y and $\pi 3_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns (RPSX) volatility to exchange rate returns (REXR).

For the selection of the orders p and q Schwarz Bayesian Information Criteria (SBIC) is used in all the above three models.

3.4. Distribution Assumptions of Residuals

Mandelbrot (1963) has argued that Normal distribution is not feasible for modeling financial returns. Because Normal distribution has characteristics of zero excess kurtosis and skewness. Whereas, probability distributions of financial returns are enriched by skewness, kurtosis greater than three, and heavy tails[2]. Therefore, to model financial returns many none Normal error distributions have been used in literature i.e. Student t distribution, Generalized Error Distribution (GED), Exponential and Gamma distributions, etc. The intended study will make use of Normal distribution and two none Normal distributions i.e. Students t and GED. These none Normal error distributions permit thicker tails relative to Normal distribution and have a property of skewness.

Normal Distribution:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \qquad -\infty < x < \infty \tag{8}$$

Student-t Distribution:

$$f(x) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{x^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, \qquad -\infty < x < \infty \tag{9}$$

v denotes the number of degrees of freedom whereas Γ denotes the gamma function.

[2] These feature are termed as leptokurtic property.

General Error Distribution:

$$f(x;\mu,\sigma,v) = \frac{\sigma^{-1} v e^{\left(-0.5\left|\frac{\left(\frac{x-\mu}{\sigma}\right)}{\lambda}\right|^{v}\right)}}{\lambda 2^{\left(1+\left(\frac{1}{v}\right)\right)} \Gamma\left(\frac{1}{v}\right)}, \qquad 1 < x < \infty \tag{10}$$

$v > 0$ denotes the degree of freedom or tail thickness parameter.

3.5. Error Metrics

To evaluate the forecasting performance of GARCH family models three error metrics have been used i.e. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE). Suppose $Y_1, Y_2, \dots, Y_h$ are actual observations whereas $\hat{Y}_1, \hat{Y}_2, \dots, \hat{Y}_h$ are forecasted values then the formula for error metrics being used in the study can be mentioned as:

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=1}^{h}(Y_t - \hat{Y}_t)^2} \tag{11}$$

$$MAE = \frac{1}{h}\sum_{t=1}^{h}\left|Y_t - \hat{Y}_t\right| \tag{12}$$

$$MAPE = \frac{1}{h}\sum_{t=1}^{h}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{13}$$

In the above equation, Y_t represent actual value while $\hat{Y}_t$ represent forecasted value. h indicates the forecast horizon. In this study, we considered dynamic forecasts.

3.6. Data

The intended study has utilized daily data from two financial markets in the context of Pakistan. Closing stock prices of the PSX-100 index as representative of the Pakistan Stock Exchange and bilateral nominal exchange rate (Pak-rupee in term of US-Dollar) representing the Currency market has been analyzed. The data spans almost 25 years. The first observation begins on August 4, 1997, and the last observation is dated April 28, 2022. A total of 6453 daily data observations have been used in the analysis. The main reason for selecting high-frequency data sets is to capture enriched information that we cannot do with low-frequency data sets. Yahoo Finance and the State Bank of Pakistan has been used as data collection source.

Figure 1a: Log of PSX 100 Index

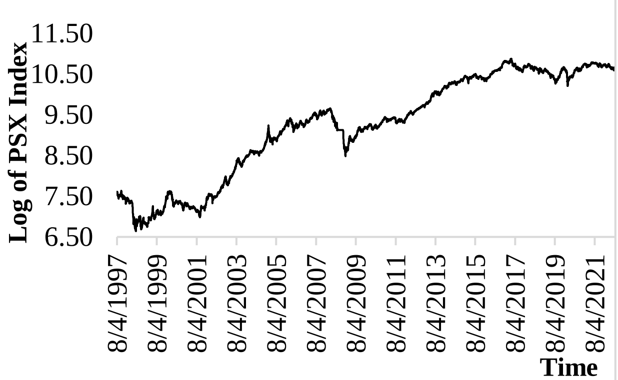
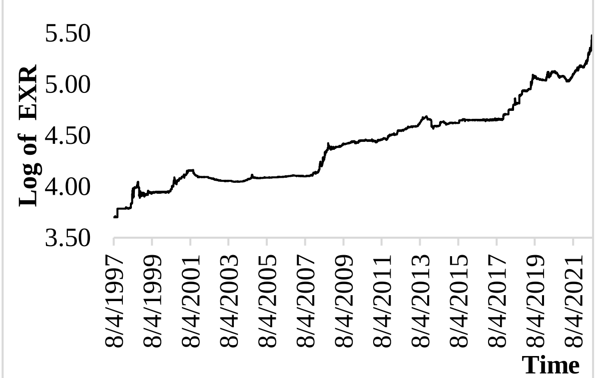


Figure 1d: Log of Exchange Rate



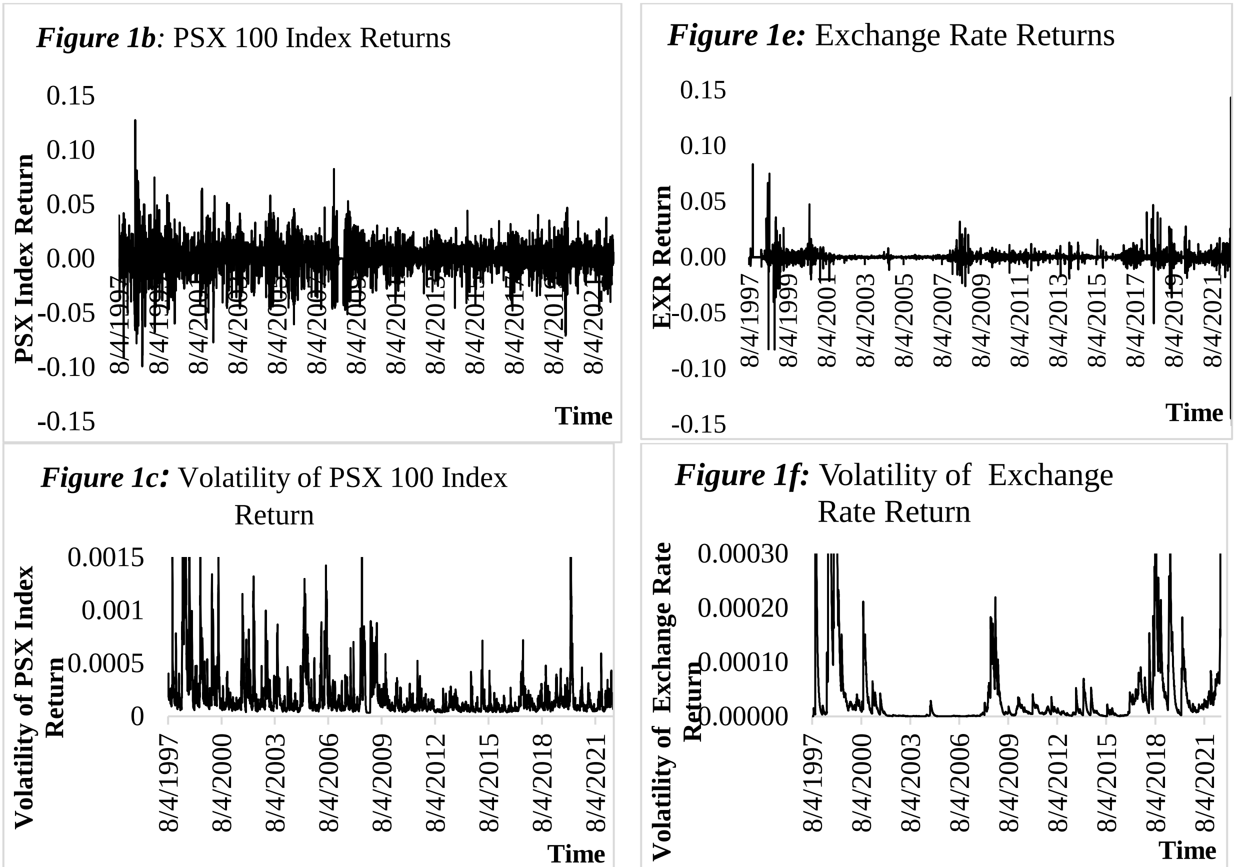


Figure 1: Graphical Analysis
Source: Authors' work.

In the above figure graph 1a and 1d, $LEXR$ and $LPSX$ portray trendy behavior with some instabilities. In the 1990s $LPSX$ it depicted plunge behavior due to a bearish trend in PSX for quite a few months. This behavior of PSX appears mainly because of economic sanctions due to a nuclear test in 1998. $LEXR$ in figure 1d is depicting a constantly rising trend due to currency depreciation in Pakistan. The figure 1b and 1c show the Pakistan Stock Exchange return ($RPSX$) and their volatility respectively. RPSX and REXR are showing high fluctuations and volatility clustering from 1999 to 2001, 2007 to 2008, and 2019 to 2020. In Figures 1d and 1f Exchange rate return ($REXR$) and its volatility is being graphed. The exchange rate also shows the same fluctuations in returns and their volatility during the same period, as shown by PSX. High fluctuations and evidence of volatility clustering show that the ARCH effect is present and hence analysis can be carried out using ARCH family models.

4. RESULTS AND DISCUSSION

Table 1 presents descriptive statistics of the logarithm and returns of the PSX-100 index and bilateral nominal exchange rate. The mean of the logarithm and growth rate of both variables is positive and not significantly different from zero. Statistics of kurtosis show that the empirical distribution of PSX and EXR return is leptokurtic. Whereas, the RPSX index is negatively skewed and REXR is positively skewed. The significance of Jarque-Bera statistics rejects the normality of both variables used in the study. Therefore, various none normal error distributions can be used for the analysis of RPSX and REXR. ARCH tests advocate the presence of heteroscedasticity in the underlying variables. Therefore, empirical analysis can be carried out using GARCH family models.

Table 1: Descriptive Statistics

Statistics	RPSX	REXR
Mean	0.00049	0.00026
Median	0.0009	0.000
Maximum	0.128	0.143
Minimum	-0.099	-0.145
Std. Dev.	0.014	0.005
Skewness	-0.413	0.437
Kurtosis	8.662	261.55
Jarque-Bera	8806.190	17977997
	(0.000)	(0.000)
ARCH-LM(50)	1170.762	1159.063
	(0.000)	(0.000)

Source: Authors' Calculations.

To determine the unit root in the data, Augmented Dickey and Fuller (1979), Phillips and Perron (1988) and KPSS unit root tests have been applied to each variable's data series involved in the analysis.

Table 2: Results of Unit Root Tests

Variables	ADF-test	PP-test	KPSS-test	Order of Integration
DLPSX	-51.069***	-73.043***	0.111	I(0)
DLEXR	-90.554***	-90.562***	0.277	I(0)

Source: Authors' calculations.

Note: Critical values for ADF and PP test at 1%, 5%, and 10% significance levels are -3.431482, -2.861925, and -2.567018 respectively. Whereas, Critical values for the KPSS test at 1%, 5%, and 10% significance levels are 0.73900, 0.46300, and 0.34700, respectively. ***, ***, ** and * indicate level of significance at 1%, 5% and 10%, respectively.

The results of the ADF, PP, and KPSS test in table 2 shows that the first differenced log of the Pakistan Stock Exchange (DLPSX) and the first differenced log of the Exchange Rate (DLEXR) are stationary. Stationarity of both variables at first difference implies that DLPSX and DLEXR are integrated of order zero I(0). After detecting evidence of a possible ARCH effect, cross-market volatility spillover is analyzed as below:

Table 3 presents results from the variance equation of the nGRACH, nEGARCH, and nGJR-GARCH models. Results from all three models advocate the existence of significant bidirectional volatility spillover between the stock market and currency markets of Pakistan. Similar results are reported by Jebran and Iqbal (2016) and Iqbal et al. (2020) for Pakistan and some Asian countries.

Table 3: Volatility Spillover across Stock Market and Currency Market based on Normal Error Distribution

Models / Coefficients	nGARCH		nEGARCH		nGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	2.53E-05*** (29.37)	4.19E-06*** (3.77)			2.31E-05*** (19.62)	2.03E-06** (1.85)
$\boldsymbol{\alpha_1}$	0.260*** (21.88)	0.174*** (23.38)			0.125*** (23.10)	0.101*** (15.03)
$\boldsymbol{\beta_1}$	0.508*** (37.64)	0.796*** (114.11)			0.042*** (3.347)	
$\boldsymbol{\beta_2}$	0.039*** (17.21)				0.468*** (17.66)	0.792*** (111.89)
$\boldsymbol{\pi 1}$	-0.008*** (-30.48)	-2.01E-07** (-1.95)			0.029*** (6.977)	
$\boldsymbol{\gamma_T}$					0.008 (0.329)	0.145*** (11.40)
$\boldsymbol{\pi 2}$					-0.008*** (-28.17)	-4.2E-07*** (-4.103)
ω			-0.093*** (-13.58)	-0.844*** (-20.12)		
$\boldsymbol{\gamma}$			0.966*** (1476.04)	0.927*** (239.30)		
$\boldsymbol{\rho}$			0.179*** (75.44)	0.314*** (27.69)		
$\boldsymbol{\theta}$			0.048*** (26.93)	-0.088*** (-13.39)		
$\boldsymbol{\pi 3}$			0.042*** (49.14)	0.004*** (2.02)		
SBIC	-7.61	-6.09	-8.63	-6.09	-7.74	-6.109
nGARCH(p, q)	nGARCH(1,2)	nGARCH(2,2)	nEGARCH(1,1)	nEGARCH(1,1)	nGJR-GARCH(2,2)	nGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	4969834 (0.000)	2445.47 (0.000)	60465479 (0.000)	5553.059 (0.000)	6025826 (0.000)	2684.100 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.255)	43.429 (0.179)	39.590 (0.093)	47.423 (0.166)	56.322 (0.132)	38.817 (0.412)
ARCH-LM (10)	0.0112 (0.325)	0.0162 (0.199)	-0.00043 (0.907)	0.0110 (0.376)	0.0155 (0.215)	0.0022 (0.859)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

In Table 4, the results of the tGARCH model advocate only unidirectional volatility spillover from $REXR \rightarrow RPSX$. However, in the case of $RPSX \rightarrow REXR$ volatility spillover disappears. A similar result was documented by Sevinç (2022) for South Korean markets. Results from tEGARCH and tGJR-GARCH models suggest bidirectional volatility spillover across both markets. Analogous results have been reported by Aftab et al. (2019) and Musa et al. (2020). The significance of the degree of freedom parameter validates the choice of Students' t distribution over normal distribution.

Table 4: Volatility Spillover across Stock Market and Currency Market based on Students t Error Distribution

Models / Coefficients	tGARCH		tEGARCH		tGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	3.53E-05*** (7.39)	-1.34E-06*** (-3.02)			2.53E-05*** (7.57)	-9.04E-06*** (-8.29)
$\boldsymbol{\alpha}$	0.150*** (6.09)	0.211*** (13.43)			0.150*** (5.60)	0.123*** (8.54)
$\boldsymbol{\beta}$	0.543*** (12.95)	0.812*** (79.19)			0.600*** (13.34)	0.804*** (85.31)
$\boldsymbol{\pi 1}$	-0.002 (-0.04)	-6.36E-07*** (-5.94)				
$\boldsymbol{\gamma_T}$					0.050 (0.83)	0.201*** (8.02)
$\boldsymbol{\pi 2}$					-0.028*** (-0.76)	-1.03E-06*** (-8.23)
ω			-0.269*** (-11.092)	-0.712*** (-13.29)		
$\boldsymbol{\gamma}$			0.994*** (1086.51)	0.953*** (185.63)		
$\boldsymbol{\rho}$			2.385*** (2.00)	0.356*** (18.41)		
$\boldsymbol{\theta}$			0.192** (1.74)	-0.098*** (-18.195)		
$\boldsymbol{\pi 3}$			-0.010*** (-4.74)	-0.004*** (-2.36)		
Degree of Freedom	20.000 (15.26)	4.778 (15.41)	2.000 (714.5)	4.889 (16.89)	20.000 (14.39)	4.959 (15.33)
SBIC	-10.157	-6.180	-10.055	-6.198	-7.61	-6.196
tGARCH(p, q)	tGARCH(1,1)	tGARCH(1,1)	tEGARCH(1,1)	tEGARCH(1,1)	tGJR-GARCH(1,1)	tGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	5810910 (0.000)	4240.46 (0.000)	26194317 (0.000)	818953.2 (0.000)	6025826 (0.000)	3827.52 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.293)	47.712 (0.199)	15.478 (0.083)	39.027 (0.161)	56.322 (0.219)	42.233 (0.186)
ARCH-LM (10)	0.0168 (2.35)	-0.006 (-2.51)	-0.002 (-2.17)	-0.003 (-2.21)	0.015 (2.26)	-0.006 (-2.48)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

Analysis of volatility spillover across the stock market and currency market based on GED distribution is presented in Table 5. Outcomes of the analysis suggest the existence of significant bidirectional volatility spillover, using gedGARCH. Similar results are reported by Iqbal et al. (2020). However, according to gedEGARCH and gedGJR-GARCH models there exist a unidirectional volatility spillover from $RPSX \rightarrow REXR$. The empirical results of the study are supported by theoretical justifications provided by flow-oriented and stock-oriented models. Appropriate lag order for the above three models is determined according to Schwarz Bayesian Information Criterion (SBIC).

Table 5: Volatility Spillover across Stock Market and Currency Market based on GED Error Distribution

Models / Coefficients	gedGARCH		gedEGARCH		gedGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	2.46E-05*** (4.555)	-1.67E-06*** (-4.029)			2.34E-08*** (3.70)	-1.06E-05*** (-14.27)
$\boldsymbol{\alpha_1}$	0.489*** (3.35)	0.189*** (13.91)			5.90*** (7.16)	0.123*** (11.47)
$\boldsymbol{\alpha_2}$					-1.84*** (-3.25)	
$\boldsymbol{\beta}$	0.589*** (8.31)	0.818*** (78.19)			0.598*** (29.46)	0.797*** (344.84)
$\boldsymbol{\pi 1}$	-0.007*** (-5.198)	-7.87E-07*** (-8.47)				
$\boldsymbol{\gamma_T}$					-0.241 (-0.42)	0.203*** (8.57)
$\boldsymbol{\pi 2}$					-1.42E-05 (-0.51)	-1.21E-06*** (-14.27)
ω			-10.054 (-1.366)	-0.813*** (14.10)		
$\boldsymbol{\gamma}$			-0.014 (-0.21)	0.941*** (172.36)		
$\boldsymbol{\rho}$			0.109 (1.39)	0.346*** (17.06)		
$\boldsymbol{\theta}$			-0.047 (-0.06)	-0.102*** (-8.37)		
$\boldsymbol{\pi 3}$			-0.043 (-0.66)	-0.005*** (-2.51)		
Degree of Freedom	2.000 (74.81)	1.215 (48.10)	0.198 (57.45)	1.192 (50.99)	2.000 (73.39)	1.217 (47.89)
SBIC	-10.106	-6.179	-10.102	-6.189	-10.22	-6.190
gedGARCH(p, q)	gedGARCH(1,1)	gedGARCH(1,1)	gedEGARCH (1,1)	gedEGARCH(1,1)	gedGJR-GARCH(2,1)	gedGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	5810910 (0.000)	3484.48 (0.000)	9570211 (0.000)	39622.73 (0.000)	6025826 (0.000)	3257.88 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.193)	46.464 (0.201)	34.070 (0.532)	43.990 (0.091)	56.322 (0.360)	46.233 (0.173)
ARCH-LM (50)	0.017 (2.35)	-0.004 (-2.50)	0.112 (2.93	-0.0003 (-2.25)	0.015 (2.24)	-0.004 (-2.33)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

The robustness of results in Tables 3, 4, and 5, is being checked by carrying out diagnostic analysis on the standardized residuals of the models. Q-statistics and ARCH test statistics are insignificant, showing that there is no ARCH effect and no autocorrelation till the 10th lag of standardized residuals. Results of Jarque-Bera test statistics confirm that residuals are non-normally distributed.

After identifying the evidence of volatility spillover across the stock market and currency markets of Pakistan, the role of returns' volatility spillover in achieving forecasting gain is analyzed. For this purpose, we utilize the information on volatility spillover to improve the forecasting performance of standard GARCH, EGARCH, and GJR-GARCH models based on Normal, Student t, and GED distributions. Forecasting results are presented in the following tables.

Table 6: Forecast Evaluation of GARCH Family Models Based on Normal Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
nGARCH						
1 Day Ahead	0.00648	0.00648	144.839	0.00631	0.00631	144.008
2 Days Ahead	0.00524	0.00519	106.713	0.00521	0.00513	106.279
3 Day Ahead	0.00593	0.00571	124.594	0.00587	0.00562	124.374
4 Days Ahead	0.00869	0.00755	103.539	0.00859	0.00748	103.255
5 Days Ahead	0.01058	0.00914	102.701	0.01044	0.00903	100.489
nEGARCH						
1 Day Ahead	0.00652	0.00652	145.907	0.00623	0.00623	138.528
2 Days Ahead	0.00534	0.00529	109.321	0.00506	0.00504	102.803
3 Day Ahead	0.00589	0.00579	125.765	0.00570	0.00571	125.143
4 Days Ahead	0.00865	0.00748	102.936	0.00854	0.00739	101.820
5 Days Ahead	0.01037	0.00909	102.999	0.01022	0.00893	101.601
nGJR-GARCH						
1 Day Ahead	0.00689	0.00689	142.431	0.00659	0.00659	142.081
2 Days Ahead	0.00529	0.00565	107.964	0.00523	0.00539	106.614
3 Day Ahead	0.00598	0.00583	124.624	0.00592	0.00579	123.966
4 Days Ahead	0.00876	0.00757	106.337	0.00868	0.00754	104.041
5 Days Ahead	0.01079	0.00938	102.182	0.01057	0.00919	101.877

Source: Authors' calculations.

Table 7: Forecast Evaluation of GARCH Family Models Based on Students t Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
tGARCH						
1 Day Ahead	0.00646	0.00646	143.703	0.00588	0.00588	130.573
2 Days Ahead	0.00525	0.00519	106.419	0.00509	0.00510	103.000
3 Day Ahead	0.00596	0.00573	125.214	0.00567	0.00553	119.827
4 Days Ahead	0.00898	0.00756	103.797	0.00876	0.00746	98.3398
5 Days Ahead	0.01070	0.00929	103.009	0.01078	0.00921	99.1100
tEGARCH						
1 Day Ahead	0.00687	0.00687	140.981	0.00591	0.00591	137.032
2 Days Ahead	0.00536	0.00568	104.664	0.00518	0.00515	103.091
3 Day Ahead	0.00578	0.00594	124.346	0.00575	0.00569	123.511
4 Days Ahead	0.00879	0.00781	103.451	0.00868	0.00772	101.991
5 Days Ahead	0.01098	0.00915	108.938	0.01053	0.00878	101.205
tGJR-GARCH						
1 Day Ahead	0.00647	0.00647	143.751	0.00641	0.00641	142.114
2 Days Ahead	0.00582	0.00517	105.818	0.00531	0.00515	105.671
3 Day Ahead	0.00597	0.00573	135.200	0.00592	0.00558	126.830
4 Days Ahead	0.00879	0.00751	102.981	0.00875	0.00749	102.409
5 Days Ahead	0.01093	0.00923	104.005	0.01066	0.00918	102.463

Source: Authors' calculations.

Table 8: Forecast Evaluation of GARCH Family Models Based on GED Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead	Without Volatility Spillover			With Volatility Spillover		
Forecast	RMSE	MAE	MAPE	RMSE	MAE	MAPE
gedGARCH						
1 Day Ahead	0.00625	0.00625	138.881	0.00624	0.00624	138.603
2 Days Ahead	0.00522	0.00516	105.186	0.00515	0.00511	104.507
3 Day Ahead	0.00575	0.00565	123.086	0.00578	0.00559	121.836
4 Days Ahead	0.00753	0.00753	101.976	0.00877	0.00755	101.807
5 Days Ahead	0.01058	0.00913	101.763	0.01058	0.00911	100.539
gedEGARCH						
1 Day Ahead	0.00659	0.00659	138.522	0.00625	0.00625	137.809
2 Days Ahead	0.00535	0.00546	109.311	0.00512	0.00509	103.973
3 Day Ahead	0.00538	0.00557	123.039	0.00522	0.00555	122.725
4 Days Ahead	0.00889	0.00790	107.352	0.00869	0.00747	100.392
5 Days Ahead	0.01099	0.00929	103.794	0.01079	0.00920	100.276
gedGJR-GARCH						
1 Day Ahead	0.00671	0.00671	140.251	0.00623	0.00623	138.526
2 Days Ahead	0.00516	0.00512	104.669	0.00512	0.00510	103.999
3 Day Ahead	0.00581	0.00561	122.287	0.00579	0.00559	121.983
4 Days Ahead	0.00873	0.00792	101.452	0.00846	0.00775	100.731
5 Days Ahead	0.01088	0.00937	101.098	0.01077	0.00928	100.473

Source: Authors' calculations.

In one of the papers, Lopez (2001) demonstrated that numerous forecast evaluation criteria can be used to evaluate the forecast performance of financial econometric models. In this study, we have used three loss functions; Root Mean Squared Error (RMSE) Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE). While taking care of information on volatility spillover across the stock market and currency market, for RPSX, forecasting accuracy of standard GARCH, EGARCH, and GJR-GARCH models is being compared in Table 6, Table 7, and Table 8 respectively. Outcomes from the above three models indicate that information on volatility spillover remains effective in improving the forecasting accuracy of stock market returns (RPSX). This comparison is made within tables 6, 7, and 8 by comparing forecasting results of RPSX with and without volatility spillover effect and highlighted in bold. These results are supported by the findings of Chatziantoniou et al. (2021) and Wu et al. (2022).

After that, we compared forecasting results of GARCH, EGARCH, and GJR-GARCH models based on Normal, Students t, and GED distribution respectively. This comparison is across tables 6, 7, and 8 with volatility spillover effect and based on distinct error distributions. According to RMSE, MAE, and MAPE, among nGARCH, tGARCH, and gedGARCH models, the tGARCH model stands out in terms of better forecasting accuracy for RPSX. Whereas, nEGARCH and gedEGARCH models performed better relative to the tEGARCH model, according to all error metrics. Among nGJR-GARCH, tGJR-GARCH, and gedGJR-GARCH models gedGJR-GARCH provides relatively more accurate forecast results for RPSX. Similar results are provided by Aftab et al. (2019) and Charfi and Mselmi (2022). Therefore, this study suggests a thoughtful implication. After considering the role of information on volatility spillover in forecasting, the family of GARCH models based on Students t and GED distributions should be considered to obtain an accurate forecast for RPSX.

Table 9: Forecast Evaluation of GARCH Family Models Based on Normal Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
nGARCH						
1 Day Ahead	0.00186	0.00186	620.667	0.00136	0.00136	260.769
2 Days Ahead	0.00349	0.00271	187.398	0.00281	0.00245	151.750
3 Day Ahead	0.00504	0.00438	373.850	0.00365	0.00283	149.437
4 Days Ahead	0.01231	0.00766	115.152	0.01160	0.00737	107.799
5 Days Ahead	0.01188	0.00731	119.034	0.01146	0.00689	102.631
nEGARCH						
1 Day Ahead	0.00076	0.00076	251.982	0.00048	0.00048	159.979
2 Days Ahead	0.00316	0.00258	166.15	0.00243	0.00197	105.043
3 Day Ahead	0.00322	0.00268	198.631	0.00291	0.00217	187.307
4 Days Ahead	0.01302	0.00799	123.04	0.01289	0.00777	121.174
5 Days Ahead	0.01159	0.00792	148.293	0.01146	0.00758	131.672
nGJR-GARCH						
1 Day Ahead	0.00185	0.00185	616.781	0.00069	0.00069	233.124
2 Days Ahead	0.00349	0.00271	189.103	0.00314	0.00246	163.905
3 Day Ahead	0.00496	0.00433	374.742	0.00366	0.00282	247.164
4 Days Ahead	0.01231	0.00766	115.152	0.01164	0.00738	107.947
5 Days Ahead	0.01291	0.00731	119.034	0.01176	0.00698	102.684

Source: Authors' calculations.

Table 10: Forecast Evaluation of GARCH Family Models Based on Student t Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
tGARCH						
1 Day Ahead	0.00073	0.00073	149.861	0.00051	0.00051	148.147
2 Days Ahead	0.00312	0.00277	109.464	0.00297	0.00271	107.194
3 Day Ahead	0.00414	0.00239	119.977	0.00367	0.00229	118.570
4 Days Ahead	0.02885	0.00799	104.653	0.01231	0.00767	102.802
5 Days Ahead	0.01147	0.00725	107.079	0.01106	0.00716	111.464
tEGARCH						
1 Day Ahead	0.00094	0.00094	204.774	0.00052	0.00052	173.269
2 Days Ahead	0.00649	0.00371	125.755	0.00350	0.00271	121.703
3 Day Ahead	0.00349	0.00269	141.035	0.00356	0.00197	134.569
4 Days Ahead	0.01478	0.00765	111.369	0.01274	0.00741	101.777
5 Days Ahead	0.01181	0.00696	122.724	0.01071	0.00546	109.835
tGJR-GARCH						
1 Day Ahead	0.00051	0.00051	156.117	0.00039	0.00039	141.653
2 Days Ahead	0.00377	0.00483	113.716	0.00350	0.00371	105.149
3 Day Ahead	0.00326	0.00244	117.588	0.00285	0.00241	113.798
4 Days Ahead	0.01179	0.00786	112.268	0.01161	0.00766	109.743
5 Days Ahead	0.01083	0.00797	119.085	0.01049	0.00731	112.415

Source: Authors' calculations.

Table 11: Forecast Evaluation of GARCH Family Models Based on GED Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
gedGARCH						
1 Day Ahead	0.00100	0.00100	133.333	0.00081	0.00081	131.742
2 Days Ahead	0.00396	0.00395	105.000	0.00379	0.00295	103.661
3 Day Ahead	0.00323	0.00227	105.183	0.00303	0.00211	101.134
4 Days Ahead	0.02387	0.00766	100.453	0.01279	0.00758	100.003
5 Days Ahead	0.01098	0.00696	101.912	0.01079	0.00678	100.992
gedEGARCH						
1 Day Ahead	0.00050	0.00050	100.999	0.00042	0.00042	100.032
2 Days Ahead	0.00497	0.00395	100.524	0.00413	0.00315	100.135
3 Day Ahead	0.00799	0.00530	100.000	0.00714	0.00486	102.145
4 Days Ahead	0.01226	0.00745	101.544	0.01180	0.00688	101.006
5 Days Ahead	0.01183	0.00698	101.797	0.01064	0.00652	101.233
gedGJR-GARCH						
1 Day Ahead	0.00150	0.00150	133.333	0.00093	0.00093	119.331
2 Days Ahead	0.00396	0.00295	100.000	0.00363	0.00298	99.6554
3 Day Ahead	0.00363	0.00277	107.183	0.00346	0.00255	105.434
4 Days Ahead	0.01183	0.00757	107.496	0.01150	0.00750	100.030
5 Days Ahead	0.01183	0.00698	109.797	0.01041	0.00642	104.173

Source: Authors' calculations.

The role of information on volatility spillover in improving the forecasting performance of GARCH, EGARCH, and GJR-GARCH models, for REXR, is being compared in Table 9, Table 10, and Table 11 respectively. For REXR, outcomes of comparison within the tables indicate that information on volatility spillover imparts remarkable predictability gain to GARCH, EGARCH, and GJR-GARCH models. This result is drawn by comparing with and without volatility spillover results for REXR forecasting. After achieving forecasting accuracy by utilizing information on volatility spillover, the role of error distributions, in forecasting REXR, is being analyzed by comparing results across tables 9, 10, and 11. Analysis shows that tGARCH and gedGARCH models provide better REXR forecasts relative to the nGARCH model. However, gedEGARCH and gedGJR-GARCH models provide better forecasts as compared to rival EGARCH models. Analogous outcomes are evidenced in Vee et al., (2011) and Kumar and Patil (2016). Hence, from the overall results of the research question we have analyzed in this section, a meaningful implication can be drawn. To improve the forecasting performance of GARCH family models, after tracing the role of information on volatility spillover in forecasting REXR, Students t, and GED distribution should be considered.

5. CONCLUSION

This study examined the returns' volatility spillover and the role of returns' volatility spillover in forecasting financial markets returns. From this perspective, this study contributed to the existing literature by analyzing the effect of information on volatility spillover along with none Normal error distributions on forecasting accuracy of standard GARCH, EGARCH, and GJR-GARCH models.

Analysis of the study from all three models indicates that there exists significant bidirectional volatility spillover across both financial markets of Pakistan. According to forecasts error metrics, information on volatility spillover effect imparts an effective role in improving the forecasting accuracy of GARCH family models based on Normal, Students t, and GED distributions, for PSX-100 index returns ($RPSX$) and bilateral nominal exchange rate returns (REXR). Moreover, we analyzed a second research question on the role of various error distributions in improving forecasting accuracy. From this viewpoint, our analysis suggests that Student t and GED error distributions should be considered to attain a relatively accurate forecast for RPSX and REXR. Therefore, it can be established from the results of the study that not only does the information on volatility spillover impart a remarkable role in improving the forecasting performance of GARCH family models but various error distributions also support forecasting accuracy gain. The outcomes of this study will provide more accurate future insight regarding financial markets to researchers, policymakers, and investors. Further research can be conducted by incorporating volatility spillover from the commodity market and bond market of Pakistan and by using multivariate financial econometric models. Furthermore, the role of some other none Normal error distributions can be examined for achieving forecasting accuracy in financial econometric models.

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Determinants of Health-Seeking Behaviour in Pakistan

ABSTRACT

Considering the low performance of Pakistan on health indices in the region, its fast-growing population, and higher poverty levels, this study aims to highlight the practical relevance of Grossman's health investment model by analyzing the health demand in Pakistan. To avoid the problem of endogeneity due to the interdependence of health capital and demand for medical care, we used the binary dependent variable. Logistic regression is employed to estimate the empirical model using microdata from Pakistan's Social & Household Integrated Economic Survey (2018-19). Results indicate that individuals with better income, education, and social respect demand more healthcare as they value a healthy lifetime high. Due to the higher cumulative risk of illness, females' health demand is higher than males. While individuals engaging in sports and recreational activities care about their anticipated future health outcomes and hence demand more healthcare. Finally, the regional control variables show that people seek fewer healthcare services in rural areas and Balochistan province due to financial constraints, lack of healthcare facilities, and transport issues.

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Author's contribution in the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

Pakistan is the sixth most populous country in the world with a growth rate of 2.4 percent and, its population stands at 207.8 million (Census, 2017). Moreover, the ranking of Pakistan on the Human Development Index is 154 out of 189 countries (HDR, 2020). The shifting demographics in Pakistan are contributing to fast population growth and higher poverty levels. Pakistan's health indices have improved slowly in the last few years. Under-5 child (infant) mortality (per 1000 live births) rate(s) have steadily declined from 252.4 (185.3) in 1960 to 67.2 (55.7) in 2019. Despite the significant improvement, these numbers are still higher than South Asia's average of 40.2 (33.1) for the year 2019. The maternal mortality rate per 100,000 live births has declined from 286 in the year 2000 to 186 in 2019 which is again higher than the regional average, 163 (The World Bank, 2020).

Out-of-pocket health expenses define an individual's or family‘s ability to fulfill their demand for healthcare (Ergete et al., 2018; Bala et al., 2022). Pakistan's out-of-pocket spending (percentage of current health expenditure) on health was 56.24 percent in 2018, 78.02 percent was the highest in 2006, and 54.87 percent was the lowest in 2002 (WHO, 2019). Looking at comparative statistics, for example, out-of-pocket spending percentages in the year 2018 for South Asia, and neighboring countries (Bangladesh, Sri Lanka, and India) were 62.36, 73.87, 50.65, and 62.67 percent, respectively. This expense, undeniably, has significantly hampered the search for adequate medical facilities in Pakistan. Life expectancy in Pakistan is lowest at 67.3 in comparison with regional countries, India (69.66), Bangladesh (72.6), Sri Lanka (76.98), and South Asia (69.6).

Such an epidemiologic transition to the predominance of non-communicable diseases is indicative of a major challenge for Pakistan’s healthcare system and requires changes in respective healthcare strategies in Pakistan. While the health system is shifted to provinces, the allocation of services and obligations to levels remains uncertain since the 18th amendment, leading to health inequalities due to inadequate and uneven allocation of resources (Nishtar et al., 2013) among the provinces. Thus, it is important to understand the factors behind the demand for medical care. Grossman’s health investment model is a standard economic theory in this regard (Grossman, 2022).

Several studies attempt to ascertain the determinants of health demand in Pakistan (Toor, & Butt, 2005; Shaikh, 2008; Akbari et al., 2009; Abbas, & Hiemenz, 2011; Malik, & Syed, 2012; Abbas & Nawaz, 2020; Mushtaq et. al., 2020) however, empirically testing the relevance of the Grossman’s model is not attempted. Considering the increase in income (real GDP per capita) in Pakistan, growth in healthcare spending can be explained by Grossman’s (1972a, 1972b, 2000) health investment model (Hall & Jones, 2007). In Grossman’s approach, inputs that produce investment in a better health status include direct expenditure on medical services (Bala et. al, 2022) and the opportunity cost of time layouts on health. Therefore, based on Grossman’s standard model assumptions, this study attempts to explore the determinants of health demand in Pakistan using the latest available microdata of the Social & Household Integrated Economic Survey (2018-2019). The study is important because understanding the determinants of health demand in Pakistan can help policymakers to distribute scarce resources effectively and efficiently. Further, the government’s intervention in the right direction would lead to increased individual welfare.

2. THEORETICAL AND EMPIRICAL MODEL

The underlying assumption of Grossman’s model states that utility is generated by the amount of healthy time $h(t)$ and the consumption of household commodities $Z(t)$. Consider the following individual’s lifetime utility function.

$$\max_{I,z,T} \int_0^T U[Z(t), h(t)]\mathrm{e}^{-\rho t}\,\mathrm{d}t \tag{1}$$

with $U(\cdot)$ and $h(\cdot)$ are differentiable, concave and strictly increasing functions. The parameter ρ represents the discount rate. The lifetime utility function can be maximized subject to the following constraints.

The health capital stock, $H(t)$, depreciates at a steady depreciation rate, $\delta(t)$, and can be upgraded by investments, $I(t)$, in health assets (Grossman, 2000). Individuals' specific health endowments which can't be controlled determine the depreciation rate.

$$\dot{H}(t) = I(t) - \delta(t)H(t) \tag{2}$$

The general form of health investment can be expressed as follows

$$I(t) = f_I\big(M(t), m(t); E(t)\big) \tag{3}$$

where, M(t), m(t), and E(t) represent the medical services, time outlays in health, and individual's knowledge in terms of total factor productivity. Furthermore, household commodities are produced according to

$$Z(t) = f_z\big(Q(t), k(t); E(t)\big) \tag{4}$$

with non-medical market goods, $Q(t)$ and consumption time, $k(t)$.
For an individual's lifetime, the budget for medical care and other market goods is restricted by initial wealth and wealth gains over time.

$$\dot{A}(t) = rA(t) + y(t) + wh(t) - C_1(t) - C_Z(t) \tag{5}$$

Wealth $A(t)$ grows over time with r rate of return, other income $y(t)$, wage w, and decrease by consuming medical care C_1 and market good C_Z. Furthermore, an individual's time constraint is given by.

$$\vartheta(t) = l(t) + m(t) + k(t) + s(t) \tag{6}$$

where $\vartheta(t) - s(t) = h(t)$. Thus, total time $\vartheta(t)$ is divided into labor time $l(t)$, time outlays in health $m(t)$, consumption time $k(t)$, and sick time $s(t)$.

Considering this theoretical model and following Nocera and Zweifel (1998) and Burggraf et al. (2016), this paper estimates the following empirical model:

$$hd_i = \beta_0 + \beta_1 edu_i + \beta_2 age_i + \beta_3 gender_i + \beta_4 hm_i + \beta_5 m_i + \beta_6 y_i + \beta_7 emps_i + \varepsilon_i \tag{7}$$

where the variables are defined in table 1 below.

3. DATA, CONSTRUCTION OF VARIABLES, & METHOD

This study uses the microdata from Pakistan's Social & Household Integrated Economic Survey (2018-19) conducted by the Pakistan Bureau of Statistics (PBS). A two-stage stratified sample design is employed in this survey. The survey provides socio-economic and demographic variables for the 24,809 households as well as personal characteristics that include employment, wages, schooling, health, hygiene, sewage, accommodation, etc. Out of 159,949 individuals, 49 percent are male and 51 percent are female, 65 percent belong to rural and 34 percent belong to urban areas. The average monthly household income is PKR 41,545 with average monthly household consumption of PKR 37,159 and per capita, monthly consumption expenditure is PKR 5959.

Information on health demand is not provided explicitly in Pakistan's Social & Household Integrated Economic (HIES) Survey. Therefore, health demand is defined as whether an individual has sought health care during the last three months, and had any household member visited a health care provider for any other reason "unrelated to illnesses". Additionally, the binary nature of the variable allows us to cater to the potential endogeneity problem due to the interdependence of health capital and demand for medical care (Burggraf et al., 2016). Keeping in view the binary nature of our outcome variable, we employ binary logistic regression to estimate the demand for health in Pakistan using the following logistic function.

$$P(Y = 1|X) = \frac{1}{1+e^{-X\beta}} \tag{8}$$

where P is the conditional probability of health care demand and X is the matrix of determinants of health (see table 1). Equation (8) can be rearranged as follows:

$$\log\left(\frac{P}{1-P}\right) = X\beta \tag{9}$$

Binary regression allows both continuous and categorical variables to predict the outcome variables with the least distributional assumption in comparison with conventional regression models like Ordinary Least Squares (OLS).

Considering the explanatory variables for the health demand function, the theoretical construct knowledge is indicated by the education which is proxied by the literacy rate (Becker, 2018). Income is an important indicator of demand for health however due to reporting and measurement biases in income, per capita consumption quintiles (Sassi et al., 2018) are used as a proxy for household income. Furthermore, consumption expenditures cater to both labor and non-labor incomes of the households as well. Denisova (2010) highlights the importance of social respect in her study of Russian adult mortality. We, therefore, based on the local norms, considered the employment categories as a proxy for social respect (Lahtinen et al., 2020). Health investment is measured by the per capita expenditure on recreational activities which positively impacts the health status and smoking is taken as a negative health investment (Heckman et al., 2018). Other control variables include provincial dummies, age, and gender of the individual.

Table 1: Variables and Definitions

Variable	Definition
$hd = \begin{cases} 1 \\ 0 \end{cases}$	Takes value one if any member of the household got sick in the last three months or visited the health center for nonmedical reasons and zero otherwise.
Age	Age is divided into three categories; below 15 years, working age (15-60), and above 60.
Edu	The literacy rate is used for the education of an individual.
m	Per capita expenditure of recreational activities is used as a health investment.
hm	Smoking is used as a negative health investment proxy.
$epms$	Employment categories: self-employed, paid employed, unpaid family helper, work in agriculture and not working.
y	Per capita consumption quintiles.
Gender	A dummy variable (Male=1, Female=2).

4. RESULTS AND DISCUSSION

Table 2 presents the estimates of the parameters identified in equations (7 & 9) above for the health demand. Logistic regression is the natural choice when studying the outcomes that are naturally or necessarily represented by a binary variable (Mood, 2010). It is evident from the results that higher income (y) tends to increase health demand which corroborates with the findings in other studies (see e.g., Cropper, 1977; Wagstaff 1986; Alam et al. 2010; Galama et al., 2012; Yoo, 2022). People with better earnings or wealth have more health reserves (Cropper, 1977) implying high consumption expenditure and a high value of healthy living which results in high demand for health (Burggraf et al., 2016; Cheah et al., 2021). Therefore, it is optimal for an individual to increase their health investment as the stock of health deteriorates with age. Our results show that the demand for health increases with age which corroborates with the positive relationship between health demand and age suggested in the literature (see e.g., Di Matteo, 2004; González-González et al., 2011; Murthy & Okunade, 2016; Blanco-Moreno et al., 2013; Lopreite & Mauro, 2017; Cheah et al., 2021).

Furthermore, education is positively and significantly associated with the increase in health demand which can be explained by the fact that knowledge E(t) determines the efficiency of health investment. The level of knowledge here is proxied by the literacy status of the individual. The studies of Wagstaff (1986), Muurinen (1982), Gerdtham & Johannesson (1999), Burggraf et al. (2016) and Yoo (2022) also support the claim that literate people are conscious about their health and hence demand more healthcare (Cheah et al., 2021; Saah et al., 2021). Moreover, literacy explains the welfare at the household level as 90 percent of the literate people fall in the richest quintile (HIES, 2018-19) in Pakistan.

Gender is intended to control biological and behavioral variation in the health demand model. Gender is significantly associated with the demand for health, female are more demanding compared to males. Hyder et al. (2005) recognize that women have a higher cumulative risk of illness than men, because of infant and maternal health complications, and significant years of life are lost leading to inadequate perinatal outcomes. Additionally, over time, a gap in male and female literacy rates is decreasing in Pakistan and the stock of knowledge E(t) for female individuals is increasing, thus resulting in a higher relative health demand.

Individuals who engage in sports and adopt healthy lifestyles tend to have higher health demands which are depicted in our results as well, lesser spending on recreational activities implies low demand for health which corroborates with the findings in Burggraf et al. (2016). Participation in recreational activities plays a key role in the well-being of the individual by reducing different health problems (Bryans, 1970). On the other hand, the health hazards of smoking lead smokers to consume more medical resources to maintain their stock of health than non-smokers thus resulting in higher demand for health (Rice et al., 1986). Variables like engaging in sports or recreational activities or smoking can be used as proxies to measure the ability of an individual to anticipate future health outcomes of today’s discretionary choices. The more they engage in sports and avoid smoking, the more they care about their anticipated future health outcomes (Burggraf et al., 2016).

Table 2: Empirical Results

	Dependent: Health Demand		
Variables	**Odds Ratio**	**Z**	**P>|z|**
Age			
≤15	1(base)	...	...
15-60	2.061	19.91	0000
≥60	4.3261	34.84	0000
Education (Edu)			
No	1 (base)	...	...
Yes	1.2161	5.18	0.000
Gender			
Male	1 (base)	...	...
Female	1.1239	6.56	0.000
Employment status (emps)			
Self-Employed	1 (base)	...	...
Paid employed	0. 6500	-10.46	0.000
Work in agriculture	0.8540	-3.09	0.002
Not working	0.8306	-4.68	0.000
Unpaid family helper	0.5860	-10.62	0.000
Smoke (hm)			
No	1(base)	...	...
Yes	1.0428	2.40	0.016
Income (y)			
Poorest	1 (base)	...	...
Second	1.1274	4.77	0.000
Middle	1.2125	7.59	0.000
Fourth	1.2647	8.83	0.000
Highest	1.3155	9.22	0.000
Recreational Expenditure (m)			
0-20	1 (base)	...	...
20-50	1.0623	2.74	0.005
50-100	1.1140	4.96	0.000
≥100	1.1728	7.10	0.000
Province			
Baluchistan	1 (base)	...	...
KPK	1.6344	14.90	0.000
Punjab	1.9642	22.56	0.000
Sindh	1.9018	20.54	0.000
Region			
Rural	1 (base)	...	...
Urban	1.0569	3.03	0.002
n=159,949	Wald chi2(29)=910.3,	Prob=0.0000	

Denisova (2010) finds that a higher self-perceived respect status significantly improves the probability of increased longevity. Following Lahtinen et al. (2020), this study considers the employment categories as a proxy for self-perceived social respect. Results indicate that self-employed being the most regarded job status in Pakistan has a higher demand for health as compared to others. Due to the presumed positive correlation between socioeconomic prosperity and self-employed job status (Gilbert et al., 2004), health demand increases, thus self-employed individuals value more to stock of health more than others (Rietveld

& Kiverstein 2014; Cheah et al., 2021). Finally, the regional control variable shows that health demand is higher in urban areas as compared to rural settlements. Rural individuals tend to seek fewer healthcare services due to financial constraints, unavailability of trained physicians, and transport issues (Douthit et al., 2015; Cheah et al., 2021; Banerjee, 2021). Provincewise comparison indicates that the health demand is least in Balochistan. Due to a lack of facilities, infrastructure, and bad law & order conditions, it is difficult to attract and retain physicians in Balochistan. Furthermore, people are financially constrained due to the highest incidence of poverty in Balochistan (Islam & Zafar, 2020).

5. CONCLUSION AND POLICY IMPLICATIONS

Considering the low performance of Pakistan on health indices relative to the neighboring countries in the region and the contribution of the shifting demographics to fast population growth and higher poverty levels, it is important to understand the factors determining the health demand in the country. Grossman's health investment model is a standard economic theory in this regard. However, it has been argued in the literature that Grossman's health investment model may fail in practical applications as the model assumes that health demand increases with higher health status. Therefore, the main aim of this study is to test the practical relevance of Grossman's health investment model in the context of Pakistan.

We employed the standard theory of Grossman to specify our empirical model. It is estimated that income significantly determines the health demand in Pakistan. People with better earning streams have a high value of healthy life and thus, invest more in their health stock (Burggraf et al., 2016; Cheah et al., 2021). It is found that health demand increases with age which is in line with the theory, health stock decreases with age. Furthermore, education is positively and significantly associated with the increase in health demand which can be explained by the fact that knowledge E(t) determines the efficiency of health investment. Literate people are conscious about their health and hence demand more healthcare. Gender is significantly associated with the demand for health, due to a higher cumulative risk of illness, females are more health demanding as compared to males (Hyder et al., 2005). Based on the findings, the government should invest in education to increase the stock of knowledge leading to better health stock. This would help to reduce the government's expenditure in the health sector. Furthermore, the female & elderly population should be the focus of all health-related policies as the demand for health is higher for them.

Individuals who engage in sports and adopt healthy lifestyles tend to have higher health demands which are depicted in our results as well, lesser spending on recreational activities implies low demand for health. The more they engage in sports and avoid smoking, the more they care about their anticipated future health outcomes (Burggraf et al., 2016). This study considers the employment categories as a proxy for self-perceived social respect (Lahtinen et al., 2020). The presumed positive correlation between socioeconomic prosperity and self-employed job status (Gilbert et al., 2004) contributes positively to health demand, thus self-employed individuals value more to the stock of health more than others (Rietveld & Kiverstein, 2014; Cheah et al., 2021). Finally, the regional control variable shows that health demand is higher in urban areas as compared to rural settlements and provincewide comparison indicates that the health demand is least in Balochistan. Hence, the place of residence has a significant impact on health-seeking behaviors (Banerjee, 2021; Cheah et al., 2021). The reasons for low health demand in rural areas and Balochistan province includes financial constraint, unavailability of trained physicians, and transport issues (Douthit et al., 2015). The provision of sports facilities at the grassroots level would not only engage our youth in healthy activities but also reduce the burden of diseases from the government's expenditure. Creating a conducive environment for entrepreneurial activities in the country provides better earning opportunities and hence better stock of health in the country.

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