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Modeling Stock Returns Volatility and Portfolio Risk Through Asset Pricing Model: Empirical Evidence from Pakistan

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Abstract:

The study aimed to test portfolio returns volatility risk from Pakistan's perspective. This research aims to evaluate the effectiveness of stock returns and portfolio risk by considering both unexpected market risk and uncertainty elements with the Fama French model and GARCH (1, 1) model. But in this study, the additional factor of liquidity of stocks is implemented in Fama French 3-Factor asset pricing model. This study explored the risk exposure posed by Rm-Rf, SMB, HML and LIQ factors and provided future direction to investors, and stakeholders to understand aggregate portfolio performance to meet risk appetite. The findings were satisfactory to support the challenging models and to deliver widespread empirical shreds of evidence to the most relevant asset pricing model for the Pakistani stock market. The GARCH (1,1) results predict future returns from past returns and developed markets have a comparative

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volatility link. The value of the likelihood statistics ratio is big, implying that the GARCH (1, 1) model is a profitable depiction of the monthly return array, which successfully and competently depicts the ordered dependency of volatility. The findings showed that the sum of GARCH (1, 1) constants for all equity profits is less than 1, which is a crucial condition for mean reversion.

Keywords: Portfolio return, Asset pricing model, Fama French 3-factor model, GARCH

1. Introduction

The basic principle of financial theories is the higher returns can be attained by taking on more risk. In this sense, most finance models and frameworks assume that investors have a risk-averse mentality, and risk premiums justify the risk-return relationship (Haqqani and Aleem, 2020).

Stock returns volatility refers to how fast the security's price changes over time. Volatility is a key notion in many economic and financial applications, modeling and anticipating volatility of financial time series has become a valuable topic for research. Volatility is defined as "the restricted variation of the original stock return" (Tsay, 2005). Volatility is often known as a form of risk. The risk in returns is assessed by the associated variance, thus investors should maintain an efficient portfolio based on mean variance with the highest possible return and a certain degree of variance. An important role in financial applications was played by volatility modeling and forecasting as for the risk management and hedging (Ahmed and Suliman, 2011).

A portfolio is an assortment of financial securities. In varied uncertain settings, portfolio investigation is a quantitative approach for categorizing an optimal portfolio that may strike equilibrium among maximizing returns and reducing risk. The issues must be resolved before choosing the optimal portfolio. "What are the return and risk of the portfolio?" If investors used common terminology like the likely gain of the portfolio to represent return and the probable loss of the portfolio to convey risk, they would not be able to quantify the return and risk of the portfolio. It would be difficult to compare portfolio return and levels of risk, let alone identify the highest return and risk. Organizations often use tools for risk management practices in the expectation of addressing the problems that arise from a quickly altering environment because organizations operate in highly vibrant markets with new and varying competitive pressures and customer desires (Raz et al., 2002). The optimum answer for controlling risks in a project portfolio is a portfolio-wide strategy (Aritua et al., 2009).

Chinese stock markets suggest that results can be impacted by both liquidity risk and liquidity itself. When employing two-phase cross-sectional regressions and unrelated regressions with data from the Shanghai stock market, the liquidity indicators used to explain stock performance varied amongst studies, revealing that assets with lower income ratios had greater predicted returns (Wei et al., 2005). Employ a Fama Macbeth regression model in the Shanghai and Shenzhen markets to demonstrate a negative correlation between revenues and cross-sectional stock returns (Zhang and Lence, 2022).

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2. Review of literature:

Fama and French (1992) the cross-sectional variation in average stock returns associated with market beta, size, leverage, book-to-market equity, and earnings-price ratios is captured by combining two readily quantifiable variables, book-to-market value and size. Additionally, even when beta is the only explanatory variable, the association between market beta and average return is flat when the analyses consider volatility in beta into account volatility in beta that is unrelated to size.

Rouwenhorst (1999) examined whether beta exposure and shared inequality due to the recession had an impact on the performance of Australian equities investors. Although it was a developed market, the Australian Stock Exchange deserved a separate study as it was smaller and more concentrated in some areas than the main developed markets. Liu and Hung (2010) predicted the use of substitute GARCH-type models to anticipate everyday volatility and to apply risk values to the Taiwanese stock index futures markets, which were the hardest hit by the global financial crisis in 2008.

Chang et al. (2011) observed the top ten crude oil companies to check the volatility spillovers between the returns on crude oil futures and the company stocks by using the VAEMA-GARCH model. Hamid et al. (2012) analyzed the usefulness of the Fama and French three-factor models in terms of asset pricing and predicted portfolio returns for stocks in Pakistan's financial sector listed on the Karachi Stock Exchange.

Hamid and Hasan (2016) described the returns and volatility behavior in the KSE returns series with non-linearity and asymmetric patterns, and modeling of volatility of the asset pricing with macroeconomic, value at risk, and semi-variance in the GARCH description. Stock returns were calculated using daily statistics from January 2000 to December 2015, whereas macroeconomic indicators were calculated using monthly data from January 2000 to December 2015. In this work, the volatility has been modeled using the GARCH and GARCH-in-mean models.

Sattar (2017) evaluated the applied implications and usefulness of the Fama French model vs the asset pricing model in explaining the excess return of the Dhaka Stock Exchange. A number of international stock markets, including China, Hong Kong, Switzerland, and Austria, had their volatility time series returns assessed by Badarla et al. (2021). The study demonstrated how volatility clusters and differences in the long- and short-term volatility effects might be found using statistical modeling. In order to develop a liquidity grounded asset pricing model that is able to explain the majority of the above anomalies more effectively than existing asset pricing models, Zhang and Lence (2022) investigated the relationship between returns and liquidity in Chinese markets.

Research Methodology:

The stock market of Pakistan served as the study's population. Empirical data of Pakistan's growing economy on monthly basis for the KSE-100 index time series were used to predict monthly market returns and for portfolio returns. This study's sample includes listed 10 top companies' stock returns data for the period of January 2016 to December 2021 by averaging

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daily values for the monthly values. The variables data are collected from the consolidated quarterly financial reports of the companies. Whereas Pakistan's T-bill 3-month rate is used as a substitution for risk free rate of return because there is no risk-free assets available in the market and that's the reason governments securities are used as proxy for risk free assets. The focus of the research is on using the asset pricing model to predict portfolio stock returns volatility and liquidity, as well as a comparison of the analytical abilities of the Asset Pricing Model for portfolio stock returns.

To calculate the return, the monthly stock value of each firm is first computed independently, and then the monthly aggregate market value of each company is calculated. Finally, the return of each month is computed by subtracting the current price of the company stock from the previous day's company stock price and dividing by the portfolio's previous day's stock price. The absolute value of the stock return is then used as a measure of price change, which indicates whether or not prices changed sharply in response to the news.

$$R_p = \frac{(P_i - P_{it-1})}{P_{it-1}}$$

The market return is also calculated as the previous return calculated by the formula given above. The expected return of the entire portfolio is estimated by investors through calculating the expected return of each investment in the portfolio as well as the total weight of each investment. The weight of each investment in the portfolio must be divided by its expected return in order to use the fundamental expected return technique. All of those figures must then be added together.

$$E(R_p) = w_1 R_1 + w_2 R_2$$

The difference between a stock's (or portfolio of stocks') return and the risk-free rate, which is often calculated using the most recent short-term Treasury bill, is known as the excess return.

$$E(R_p - R_f) = \text{Excess Portfolio Returns}$$

SMALL MINUS BIG (SMB)

The size impact known as Small Minus Big (SMB) is based on a company's market capitalization. The historic performance of small-cap enterprises over large-cap corporations is measured by SMB.

Market Capitalization = Current Market Price per share * Total Number of Outstanding Shares.

$$\mathbf{SMB = 1/2(Small\ Low + Small\ High) - 1/2(Big\ Low + Big\ High)}$$

HIGH MINUS LOW (HML)

High Minus Low is a value premium (HML). This ratio illustrates the difference in returns between companies with a high book-to-market value ratio (value companies) and those with a

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low book-to-market value ratio. According to the HML factor, value companies (those with a high book-to-market ratio) have longer-term greater returns than growth stocks (low book-to-market ratio).

$$\mathbf{HML = 1/2(Small\ High + Big\ High) - 1/2\ (Small\ Low + Big\ Low)}$$

LIQUIDITY (LIQ)

Conversely, the stock market offers a higher degree of market liquidity. If an exchange has a sizable volume of transactions that are not dominated by selling, the price a buyer offers per share (the bid price) and the price a seller is willing to accept (the ask price) will be relatively near to one another. Consequently, in return for a swift sell, investors won't have to give up unrealised gains.

After that, stock returns are divided into ratios: The number of stocks returns absolute value is divided by that time period's volume traded. Finally, Liquidity is calculated as follows:

$$\text{Liquidity} = \frac{|\text{Rt}|}{\text{Volume d}}$$

Where, $|\text{Rt}|$ = Absolute value of the stock return; Volume d = Volume of that stock traded time period

Subsequently, the stock values are arranged in descending order by month. Two equally weighted portfolios were created based on those classifications: the low-liquidity portfolio, LL, is made up of 50% equities with the lowest liquidity, and the high-liquidity portfolio, HL, is made up of 50% companies with the highest liquidity. Afterwards, construct the monthly earnings as the liquidity replicating factor LIQ.

$$\text{LIQUIDITY} = 1/2\ (\text{Small High} + \text{Big High}) - 1/2\ (\text{Small Low} + \text{Big Low})$$

Data analysis and model specification

This study has extended the previous studies conducted in Pakistan and used formal procedures to model the volatility of stock returns and portfolio risk through the asset pricing model. One way is the Regression Analysis to check the validity and applicability of the Fama French 3-Factor model.

Table 1 shows the results of descriptive summary statistics of independent and dependent variables, it shows that the performance of individual variables varies widely. For example, SMB variable has the highest average return mean value of 0.004 and LIQ has the lowest average return mean value of 0.000. Moreover, the median value was the same for the market premium (R_m-R_f) and liquidity (LIQ) variable which was 0.002 whereas; it was lowest for the HML -0.009. Similarly, the variable measured in the Fama French model the market premium (R_m-R_f) has a maximum return of 0.387 whereas the minimum return was -0.234. The mean average return value of the same variable was 0.003 and median value was 0.002 it also got the highest standard deviation which was 0.093.

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From the summary data analysis if we combine them for result the lowest average value for portfolio average return -0.006 of portfolio P26 and the highest portfolio average return value 0.008 of portfolio P31 was shown in the table. Moreover, the median average values for this column were highest at 0.009 of P43 and lowest at -0.017 of P24. The maximum observation's returns highest value was 0.449 of P36, whereas the minimum observation's returns highest value was -0.189 of P24. To look up the portfolio returns in terms of riskiness or volatility the highest value of volatility was observed at 0.125 of P39 whereas the lowest value of volatility in portfolio returns was at 0.082, it was the same for the P11 and P5.

The Leptokurtic pattern, which implies a positive excess kurtosis, was shown by the kurtosis values exceeding 3. Heavy tails on each side of the leptokurtic distribution indicate significant outliers. A leptokurtic distribution used in this study shows that the investment returns may be skewed towards negative or positive values. Thus, a potentially hazardous investment is one whose returns follow a leptokurtic distribution.

The portfolio return distribution shows a positive skewness, investors can expect recurrent small losses and few large returns from stock. Contrariwise, a negatively skewed distribution suggests many small wins and a few large losses on the stock. As the only portfolio P36 was negatively skewed -0.022. None of the variables followed normal distribution as the $R_M\_R_F$ and SMB were positively skewed and HML and LIQ were negatively skewed with a kurtosis value greater than 3. These results followed the same descriptive pattern shown by the study done on the Fama French 3-factor model (Rashid et al. 2018)

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Table 1: Descriptive statistics of Portfolio Returns (P1- P45)

	Mean	Median	Maxi.	Mini.	Std. Dev.	Skewness	Kurtosis	Obs.
RM_RF	0.003	0.002	0.387	-0.234	0.093	0.823	6.831	71
SMB	0.004	-0.002	0.118	-0.111	0.046	0.352	3.339	71
HML	-0.002	-0.009	0.138	-0.232	0.056	-0.533	6.229	71
LIQUIDITY	0	0.002	0.068	-0.106	0.03	-0.537	4.306	71
P1	-0.002	-0.011	0.356	-0.235	0.085	0.947	6.845	71
P2	-0.003	-0.008	0.344	-0.245	0.097	0.588	5.286	71
P3	-0.003	-0.011	0.33	-0.2	0.089	0.761	5.086	71
P4	0.002	0.006	0.355	-0.213	0.098	0.829	4.843	71
P5	-0.003	-0.013	0.314	-0.213	0.082	0.599	5.743	71
P6	-0.002	-0.013	0.41	-0.247	0.099	0.875	6.65	71
P7	0.005	-0.004	0.365	-0.219	0.095	0.629	5.205	71
P8	0	-0.007	0.379	-0.25	0.103	0.639	4.958	71
P9	-0.001	0.007	0.314	-0.27	0.09	0.268	5.047	71
P10	0.001	-0.005	0.371	-0.202	0.095	1.007	5.656	71
P11	-0.005	-0.016	0.33	-0.261	0.082	0.643	6.979	71
P12	-0.004	-0.014	0.425	-0.241	0.099	1.064	7.912	71
P13	0.003	-0.001	0.381	-0.205	0.094	0.748	5.99	71
P14	-0.002	-0.007	0.395	-0.242	0.1	0.785	5.952	71
P15	-0.002	-0.006	0.33	-0.251	0.088	0.447	5.621	71
P16	-0.004	-0.009	0.36	-0.242	0.095	0.654	6.011	71
P17	-0.005	-0.013	0.334	-0.297	0.102	0.543	5.089	71
P18	0	-0.003	0.375	-0.296	0.113	0.561	5.002	71
P19	-0.005	-0.009	0.318	-0.294	0.097	0.384	5.514	71
P20	-0.004	-0.006	0.414	-0.347	0.111	0.468	6.039	71
P21	0.003	0.001	0.369	-0.319	0.108	0.461	5.395	71
P22	-0.002	0.001	0.383	-0.351	0.115	0.458	5.16	71
P23	-0.003	-0.002	0.319	-0.371	0.11	0.04	4.937	71
P24	-0.005	-0.017	0.346	-0.189	0.088	0.999	5.948	71
P25	0	-0.016	0.345	-0.247	0.103	0.782	4.848	71
P26	-0.006	-0.007	0.304	-0.245	0.087	0.522	5.296	71
P27	-0.004	-0.006	0.4	-0.299	0.105	0.735	6.155	71
P28	0.002	0.003	0.355	-0.271	0.1	0.532	5.022	71
P29	-0.002	-0.008	0.369	-0.302	0.108	0.553	4.748	71
P30	-0.003	-0.005	0.304	-0.322	0.096	0.132	5.112	71
P31	0.008	0.004	0.38	-0.27	0.106	0.702	5.284	71
P32	0	-0.008	0.329	-0.244	0.095	0.672	5.103	71

P33	-0.004	-0.008	0.384	-0.296	0.097	0.537	6.61	71
P34	0.002	-0.001	0.339	-0.268	0.095	0.402	5.095	71
	Mean	**Median**	**Maxi.**	**Mini.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Obs.**
P35	-0.003	-0.008	0.353	-0.299	0.1	0.364	5.128	71
P36	-0.003	-0.005	0.288	-0.319	0.089	-0.022	5.637	71
P37	0.001	-0.005	0.425	-0.297	0.11	0.863	6.188	71
P38	0.004	0.006	0.435	-0.321	0.116	0.555	5.386	71
P39	-0.001	-0.004	0.449	-0.353	0.125	0.6	5.196	71
P40	-0.002	0.005	0.384	-0.373	0.106	0.15	6.206	71
P41	0.003	0.001	0.394	-0.301	0.113	0.687	4.993	71
P42	0.005	-0.003	0.404	-0.325	0.12	0.39	4.277	71
P43	0	0.009	0.354	-0.376	0.11	0.092	5.199	71
P44	0.002	0	0.33	-0.321	0.105	0.172	4.571	71
P45	0.005	0	0.339	-0.345	0.104	0.057	5.077	71

Regression Analysis of Portfolio Returns of Fama French 4-Factor Model

To model volatility and liquidity with the asset pricing model it was required to first add liquidity in the asset pricing model, so the regression of the Fama French 3-Fcator model has to be modeled with an additional liquidity factor in it. Table 2 the regression of the Fama French 4-Factor model the additional liquidity variable's coefficient was represented by the $\tilde{l}$ symbol.
Three risk acquaintances one a market component, and the other two firm-specific traits make up the explanatory factors. The market component is also referred to as the equity premium or market excess return, which is the market return on the excess of RFR. The twofold sorting strategy (2x2) is used to build portfolios for the other two exploratory criteria. The sample stocks are separated into two-size portfolios (small and big) and then into two portfolios based on B/M for each size portfolio (growth and value). The fourth portfolio for the factor liquidity has been shaped using the same methodology; the only variation is that the second sorting variable, liquidity (high and illiquid), has been employed. The general designations for the value, size, and liquidity factors are HML, SMB, and LIQ.

The theory is predicated on the observation that illiquid, high-value, small-cap companies routinely outperform the overall market.

$$\mathbf{R_p - R_f = \tilde{\alpha} + \tilde{b}(R_m - R_f) + \tilde{s}(SMB) + \tilde{h}(HML) + \varepsilon_t} \quad (1)$$

The additional factor that is added to this model is liquidity of stocks.

$$\mathbf{R_p - R_f = \tilde{\alpha} + \tilde{b}\,(R_m - R_f) + \tilde{s}(SMB) + \tilde{h}(HML) + \tilde{l}(LIQ) + \varepsilon_t} \quad (2)$$

For the Fama French 4-Factor model, the excess return of each portfolio stock was utilized to run regression against the market excess return as well as against the market risk premium, size premium, value premium, and liquidity premium. With a 95% confidence level, the regression analysis's alpha (Level of Significance) was set at 5%. The alpha of the slope line shows positive values for thirteen portfolios and the remaining portfolios show negative values this demonstrates that constant alpha has a mostly negative relationship with dependent variables. The lowest value of alpha constant was -0.008 for P26 and the p-value was 0.035 which is less than 5%.

The p-value displays that it has a significant impact on the dependent variable as this constant shows the difference in the slope market line. Moreover, this was the only value in a table that shows significant value. The highest value of this constant was 0.000 and has a p-value of 0.999 of the P4, which was not significant.

The next important coefficient was of market risk premium ($\tilde{b}$), the values of coefficients were positive which means these values display positive change in the dependent variable. The lowest beta coefficient value of 0.940 of P1 has a p-value of 0.000 which was significant. The highest coefficient value 1.154 of P31 has a p-value 0.000 which is also significant as it was below the 5% level. When the entire table checked for the p-values of market risk premium the 0.000 significance level was witnessed, so it was seen that all the coefficients were significant. For every stock when the Fama French model was used, the beta for the market index decreased, with the exception of P32, P26, P4, P3, and P25. It was hinted that market portfolio, which the Fama French model addressed, is not the only element that might explain variability in stock return. This study produced similar findings, with only one out of five companies exhibiting contrary behaviour (Sattar, 2017).

The coefficients of SMB mostly have negative relationship with dependent variable i-e portfolio returns. Few positive values were observed whereas these values followed non-significant p-values. The lowest value of coefficient was -0.464 has the p-value 0.009 of P42 followed by the next second lowest beta value -0.420 has the p-value 0.001 of P21. The highest value of beta was 0.186 has the p-value 0.133 of P25, which was non-significant. This 4-factor regression also showed the same results as previous 3-factor regression, as it represented that small size companies outperformed the large size companies. The ¾ of the portfolios has the p-value below the significance level that means these coefficients values show important part in determine portfolio returns.

Table 2: Regression of Fama French 4-Factor Model for Portfolio Returns (1- 45 Portfolios)

$$R_p - R_f = \tilde{\alpha} + \tilde{b}(R_m - R_f) + \tilde{s}(SMB) + \tilde{h}(HML) + \tilde{l}(LIQ) + \varepsilon_t$$

	$\tilde{\alpha}$	$\tilde{b}$	$\tilde{s}$	$\tilde{h}$	$\tilde{l}$	R^2
P1	-0.004	0.940	-0.168	-0.282	-0.406	0.821
p-value	0.316	0.000	0.131	0.013	0.009	
P2	-0.004	0.971	-0.208	0.067	-0.374	0.872
p-value	0.357	0.000	0.056	0.536	0.014	
P3	-0.005	0.861	0.075	0.049	-0.380	0.886
p-value	0.146	0.000	0.420	0.594	0.004	
P4	0.000	0.913	0.061	0.120	-0.187	0.847

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p-value	0.999	0.000	0.604	0.312	0.252	
P5	-0.005	0.863	-0.098	-0.056	-0.091	0.885
p-value	0.141	0.000	0.252	0.513	0.438	
P6	-0.004	1.044	-0.207	-0.036	-0.532	0.907
p-value	0.341	0.000	0.029	0.701	0.000	
P7	0.003	0.994	-0.262	-0.072	-0.270	0.842
p-value	0.475	0.000	0.026	0.534	0.095	
P8	-0.001	1.021	-0.253	0.101	-0.571	0.897
p-value	0.771	0.000	0.015	0.325	0.000	
P9	-0.002	0.893	-0.205	0.096	-0.272	0.879
p-value	0.642	0.000	0.036	0.323	0.045	
P10	-0.002	0.941	-0.057	0.022	0.069	0.830
p-value	0.753	0.000	0.639	0.858	0.680	
P11	-0.007	0.891	-0.215	-0.154	0.165	0.841
p-value	0.103	0.000	0.034	0.128	0.235	
P12	-0.005	1.073	-0.324	-0.134	-0.277	0.859
p-value	0.266	0.000	0.006	0.244	0.083	
P13	0.002	1.023	-0.380	-0.170	-0.014	0.818
p-value	0.716	0.000	0.003	0.169	0.933	
P14	-0.003	1.049	-0.370	0.003	-0.315	0.874
p-value	0.537	0.000	0.001	0.981	0.040	
P15	-0.003	0.922	-0.323	-0.002	-0.016	0.859
p-value	0.416	0.000	0.002	0.984	0.910	
P16		0.999	-0.326	-0.031	-0.118	0.858
p-value	0.215	0.000	0.004	0.776	0.440	
P17	-0.006	0.921	-0.083	0.300	-0.091	0.877
p-value	0.146	0.000	0.452	0.008	0.551	
P18	-0.001	0.973	-0.096	0.370	0.102	0.821
p-value	0.860	0.000	0.512	0.014	0.616	
	$\tilde{a}$	**$\tilde{b}$**	**$\tilde{s}$**	**$\tilde{h}$**	**$\tilde{l}$**	**R^2**
P19	-0.006	0.923	-0.255	0.195	0.198	0.856
p-value	0.181	0.000	0.026	0.089	0.208	
P20	-0.005	1.104	-0.364	0.215	-0.244	0.933
p-value	0.193	0.000	0.000	0.017	0.048	
P21	0.002	1.054	-0.420	0.178	0.019	0.855
p-value	0.652	0.000	0.001	0.161	0.915	
P22	-0.002	1.081	-0.410	0.351	-0.283	0.911
p-value	0.600	0.000	0.000	0.001	0.057	
P23	-0.003	0.953	-0.363	0.346	0.017	0.788

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p-value	0.649	0.000	0.022	**0.029**	0.937	
P24	-0.007	0.889	-0.043	-0.048	-0.124	0.832
p-value	0.121	0.000	0.697	0.663	0.421	
P25	-0.002	0.863	0.186	0.353	0.096	0.851
p-value	0.613	0.000	0.133	0.005	0.572	
P26	-0.008	0.813	0.027	0.178	0.192	0.891
p-value	0.035	0.000	0.756	0.047	0.118	
P27	-0.006	0.994	-0.082	0.198	-0.250	0.885
p-value	0.170	0.000	0.456	0.076	0.103	
P28	0.001	0.944	-0.137	0.161	0.013	0.837
p-value	0.867	0.000	0.269	0.197	0.941	
P29	-0.004	0.971	-0.128	0.334	-0.289	0.884
p-value	0.420	0.000	0.262	0.004	0.069	
P30	-0.004	0.843	-0.080	0.329	0.011	0.872
p-value	0.311	0.000	0.446	0.003	0.940	
P31	0.006	0.996	-0.151	0.231	0.205	0.863
p-value	0.199	0.000	0.213	0.059	0.221	
P32	-0.002	0.864	0.014	0.248	0.384	0.878
p-value	0.603	0.000	0.893	0.018	0.008	
P33	-0.006	0.996	-0.254	0.092	0.039	0.907
p-value	0.120	0.000	0.006	0.311	0.757	
P34	0.001	0.946	-0.309	0.056	0.301	0.827
p-value	0.806	0.000	0.012	0.645	0.075	
P35	-0.003	0.973	-0.300	0.229	0.000	0.901
p-value	0.395	0.000	0.003	0.021	0.999	
P36	-0.004	0.845	-0.252	0.224	0.299	0.877
p-value	0.310	0.000	0.010	0.023	0.027	
P37	-0.001	1.046	-0.095	0.268	-0.057	0.914
p-value	0.871	0.000	0.339	0.009	0.679	
P38	0.003	1.127	-0.418	0.076	-0.140	0.782
p-value	0.689	0.000	0.014	0.650	0.543	

	ã	**b̃**	**s̃**	**h̃**	**Ĩ**	**R^2**
P39	-0.002	1.154	-0.409	0.249	-0.441	0.819
p-value	0.780	0.000	0.015	0.134	0.055	
P40	-0.002	1.026	-0.362	0.244	-0.142	0.903
p-value	0.547	0.000	0.001	0.019	0.313	
P41	0.002	1.022	-0.141	0.404	-0.096	0.922
p-value	0.654	0.000	0.148	0.000	0.475	
P42	0.005	1.104	-0.464	0.212	-0.179	0.778

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p-value	0.468	0.000	0.009	0.226	0.457	
P43	0.000	1.003	-0.407	0.380	-0.181	0.893
p-value	0.990	0.000	0.001	0.001	0.241	
P44	0.001	0.895	-0.094	0.399	0.204	0.834
p-value	0.831	0.000	0.478	0.004	0.268	
P45	0.004	0.976	-0.417	0.207	0.120	0.812
p-value	0.425	0.000	0.004	0.139	0.531	

When analyzing the HML beta coefficient 10 portfolios had shown negative relationship with dependent variable. The lowest value of h̃ -0.282 of P42 and has the p-value 0.013, so it was significant in determining the portfolio return. Whereas the highest value of h̃ 0.404 of P32 has the p-value 0.000, this value was significant and expresses the positive relation with portfolio returns. When p-values were examined it was perceived that only 18 portfolios out of 45 were revealed significant relationship whereas all other were insignificant. Moreover the lowest p-value portfolios was P32 has the beta value 0.404.

The valuation of the role of liquidity risk in asset pricing is frequent in financial literature. However, studies on this relationship in the context of emerging markets were rare (Carvalho, 2022). The additional factor of liquidity represented with l̃ symbol. The positive coefficient values were displayed by 18 portfolios and the remaining portfolios revealed the negative value of liquidity. The highest sensitivity coefficient value of liquidity was 0.384 of P32 which has the p-value 0.008 and it was significant. The lowest value of this liquidity coefficient -0.571 of P8 and it has a p-value 0.000 which was also significant. If the results were drawn on the p-value only 10 portfolios have the significant p-value and the remaining portfolios were insignificant. The highest value of R2 means that model can explain the highest level of 93% of the given data set. The lowest value of R-Square (R2) was 0.778 of P42 and the highest was value 0.933 of P20. The R^2 clearly shows that 0.778 and 0.933 (78% to 93%) of portfolio stock return variation of portfolio P42 and P20 can be explained by the variation of an independent variable (excess return) while the rest 22% and 7% were influenced by other factors that were not revealed in this study.

GARCH (1, 1) Model for Portfolio Returns Analysis

The modeling of financial time series is a key area of study and application of probability theory. Heteroscedasticity effects are a unique set of issues associated with this topic; they suggest that the volatility of the mechanism being studied is often not consistent. This model, in particular the more straightforward GARCH (1, 1) model, has found widespread application in the modeling of financial time series and is supported by the majority of statistical and econometric software programs. GARCH methods are a strategy to research how to build and map a function of past returns onto the second instant in a particular financial series (Hull and White, 2000).

In this case, the volatility is calculated as a square root of the conditional variance of the log return process divided by its previous values. In simpler terms, if Pt is the time series evaluated

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at time t, then one defines the log returns. σ2t can have an additional autoregressive structure within itself according to Tim Bollerslev's (1986) extension of the ARCH model. The generalised ARCH (1, 1) model is represented by the following:

Mean equation

$$P_t = c + \rho P_t - 1 + \epsilon t$$

$$R_p = \theta + \varepsilon_t \, where \, \varepsilon_t | \, \sigma_{t-1} N(0, h_t)$$

Variance equation

$$ht \; = \; \varphi + \sum_{j=1}^{1} \delta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{1} \beta_i h_{t-1} + \; \alpha\left(R_m - R_f\right) + \omega(SMB) + \gamma(HML) + \pi(LIQ)$$

Where:

The constant is represented by φ, the parameters for the ARCH and GARCH effects, respectively, by δ_j and β_ide. The number of lags for the square error terms and conditional variance, respectively, is indicated by p and q.

The primary reason for utilising volatility as a risk measurement tool is that it is thought to be helpful in cases where the analysis's projected portfolio returns follow a normal distribution (Tegtmeier, 2022). In the field of finance, return volatility was also deemed significant due to its impact on asset pricing, portfolio construction, and market risk measurement (Andersen et al., 2006).

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Table 3(a) GARCH (1, 1) Model for portfolio Returns

Mean Equation																				
	P1		**P2**		**P3**		**P4**		**P5**		**P6**		**P7**		**P8**		**P9**		**P10**	
Variable	**C**	**P**	**c**	**p**	**c**	**p**	**C**	**p**	**c**	**p**	**c**	**P**	**c**	**p**	**c**	**p**	**C**	**p**	**c**	**P**
C	0.001	0.968	0.019	0.146	0.006	0.608	0.003	0.784	-0.001	0.894	0.000	0.980	0.002	0.838	-0.006	0.679	0.015	0.000	0.006	0.257
P(-1)	0.020	0.903	0.362	0.004	0.118	0.250	0.319	0.012	0.265	0.008	0.073	0.444	0.240	0.008	0.131	0.200	0.360	0.000	0.435	0.000
Variance Equation																				
C	0.003	0.158	0.002	0.182	0.002	0.322	0.002	0.164	0.001	0.365	0.001	0.219	0.001	0.000	0.002	0.222	0.001	0.013	0.003	0.000
RESID(-1)^2	0.034	0.000	0.245	0.173	0.096	0.156	0.339	0.146	0.273	0.071	0.200	0.042	0.255	0.004	0.171	0.175	0.206	0.130	0.557	0.014
GARCH(-1)	0.581	0.017	0.499	0.045	0.567	0.080	0.348	0.213	0.570	0.000	0.511	0.041	0.533	0.000	0.554	0.064	0.571	0.002	0.096	0.312
RM_RF(α)	0.004	0.743	0.010	0.554	0.005	0.688	-0.006	0.819	-0.001	0.944	-0.009	0.426	-0.020	0.132	0.002	0.879	-0.007	0.602	-0.050	0.012
SMB(ω)	-0.020	0.444	-0.041	0.448	0.003	0.876	0.025	0.583	-0.003	0.847	0.012	0.500	0.025	0.035	-0.021	0.535	0.005	0.868	0.087	0.015
HML(γ)	-0.057	0.017	-0.037	0.169	-0.029	0.087	-0.028	0.592	-0.032	0.039	-0.027	0.138	-0.020	0.178	-0.045	0.099	-0.031	0.132	0.037	0.173
LIQ (π)	0.029	0.454	-0.020	0.000	0.046	0.177	0.002	0.963	-0.020	0.110	-0.046	0.105	-0.080	0.004	-0.047	0.195	-0.037	0.139	0.071	0.003
Diagnostic Test																				
R-squared	0.003		-0.060		0.013		0.038		0.041		0.015		0.069		0.013		-0.035		-0.023	
Log likelihood	81.398		75.712		82.505		73.029		91.778		85.595		85.047		74.045		85.550		79.907	
Durbin-Wats. stat	1.767		2.322		1.906		2.269		2.144		1.840		1.974		1.985		2.269		2.539	
Akaike info cri.	-2.069		-1.906		-2.100		-1.829		-2.365		-2.188		-2.173		-1.858		-2.187		-2.026	
Schwarz cri.	-1.779		-1.617		-1.811		-1.540		-2.076		-1.899		-1.884		-1.569		-1.898		-1.737	
Hannan-Quinn cri.	-1.954		-1.791		-1.985		-1.715		-2.250		-2.074		-2.058		-1.744		-2.072		-1.911	

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Table 3(b) GARCH (1, 1) Model for portfolio Returns

Variable	**P11**		**P12**		**P13**		**P14**		**P15**		**P16**		**P17**		**P18**		**P19**		**P20**	
	C	**p**	**c**	**p**	**c**	**p**	**C**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**P**
Mean Equation																				
C	0.013	0.418	0.009	0.484	0.005	0.595	0.000	0.997	0.011	0.263	-0.004	0.885	-0.011	0.382	-0.001	0.974	-0.007	0.684	0.009	0.706
P1(-1)	0.223	0.167	0.177	0.192	0.145	0.080	0.035	0.756	0.159	0.193	0.079	0.758	0.074	0.542	0.172	0.408	0.080	0.479	0.112	0.535
Variance Equation																				
C	0.004	0.214	0.005	0.122	0.002	0.012	0.003	0.275	0.001	0.287	0.008	0.321	0.001	0.324	0.012	0.367	0.006	0.186	0.009	0.199
RESID(-1)^2	0.200	0.365	0.292	0.090	0.143	0.001	0.136	0.266	0.208	0.122	-0.122	0.001	0.106	0.103	-0.149	0.101	-0.107	0.184	0.089	0.611
GARCH(-1)	0.444	0.200	0.372	0.312	0.560	0.000	0.550	0.142	0.616	0.003	0.592	0.231	0.742	0.000	0.595	0.250	0.575	0.103	0.578	0.109
RM_RF(α)	0.008	0.593	-0.011	0.818	-0.004	0.467	0.001	0.941	-0.010	0.571	0.000	0.989	-0.007	0.086	0.000	0.996	0.005	0.346	-0.003	0.944
SMB(ω)	-0.036	0.241	-0.055	0.237	0.005	0.268	-0.027	0.424	0.015	0.540	-0.014	0.812	0.003	0.834	-0.001	0.993	-0.018	0.511	-0.149	0.233
HML(γ)	-0.055	0.202	-0.025	0.667	-0.039	0.000	-0.041	0.127	-0.022	0.337	-0.002	0.964	0.006	0.689	0.000	0.998	-0.003	0.872	-0.013	0.840
LIQUIDITY(π)	0.013	0.689	0.022	0.628	-0.072	0.009	-0.038	0.193	-0.012	0.762	0.009	0.949	0.083	0.010	0.003	0.985	0.083	0.117	0.029	0.000
Diagnostic Test																				
R-squared	-0.025		-0.006		0.048		0.006		-0.011		0.010		0.011		0.039		0.021		-0.003	
Log likelihood	85.183		78.462		84.203		76.593		82.206		63.878		69.734		51.107		68.932		58.295	
Durbin-Watson stat	2.093		2.074		1.803		1.858		2.039		1.956		1.882		1.991		1.831		1.999	
Akaike info criterion	-2.177		-1.985		-2.149		-1.931		-2.092		-1.568		-1.735		-1.203		-1.712		-1.408	
Schwarz criterion	-1.888		-1.696		-1.860		-1.642		-1.803		-1.279		-1.446		-0.914		-1.423		-1.119	
Hannan-Quinn criterion.	-2.062		-1.870		-2.034		-1.816		-1.977		-1.453		-1.620		-1.088		-1.598		-1.294	

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Table 3(c) GARCH (1, 1) Model for portfolio Returns

Variable	P21		P22		P23		P24		P25		P26		P27		P28		P29		P30	
	c	P	c	p	c	P	c	p	c	p	c	p	c	p	c	p	c	p	c	P
Mean Equation																				
C	0.004	0.744	0.030	0.078	0.006	0.570	-0.005	0.656	-0.003	0.764	-0.002	0.865	0.000	0.978	0.009	0.450	0.010	0.240	0.006	0.463
P1(-1)	0.224	0.052	0.089	0.573	-0.033	0.817	0.078	0.049	0.309	0.006	0.230	0.100	0.139	0.233	0.415	0.001	0.103	0.381	0.163	0.198
Variance Equation																				
C	0.002	0.107	0.004	0.064	0.007	0.192	0.002	0.074	0.002	0.357	0.001	0.296	0.002	0.175	0.001	0.181	0.002	0.201	0.001	0.111
RESID(-1)^2	0.161	0.164	0.142	0.369	-0.067	0.105	0.116	0.175	0.149	0.195	0.225	0.232	0.194	0.151	0.223	0.110	0.201	0.177	0.155	0.000
GARCH(-1)	0.553	0.006	0.543	0.107	0.568	0.157	0.563	0.003	0.666	0.005	0.560	0.070	0.536	0.015	0.598	0.005	0.571	0.005	0.661	0.000
RM_RF(α)	0.000	0.993	0.013	0.031	0.015	0.403	0.002	0.896	-0.009	0.725	-0.012	0.505	-0.011	0.000	-0.025	0.080	-0.006	0.519	-0.009	0.369
SMB(ω)	0.046	0.029	-0.086	0.016	-0.066	0.238	0.019	0.409	0.025	0.522	0.023	0.394	0.043	0.009	0.032	0.214	0.039	0.067	0.042	0.010
HML(γ)	-0.034	0.160	-0.042	0.014	-0.024	0.374	-0.047	0.116	0.004	0.894	-0.003	0.920	-0.047	0.099	-0.005	0.854	-0.042	0.103	-0.030	0.130
LIQUIDITY(π)	-0.064	0.106	-0.040	0.612	0.083	0.134	-0.030	0.449	0.094	0.060	0.024	0.540	-0.073	0.169	-0.060	0.298	-0.075	0.075	-0.024	0.573
Diagnostic Test																				
R-squared	0.043		-0.072		-0.017		0.008		0.028		0.018		0.007		0.012		-0.006		0.010	
Log likelihood	71.577		60.815		61.938		83.768		70.666		81.539		80.001		77.939		73.899		77.906	
Durbin-Watson stat	2.067		1.869		1.659		1.988		2.248		2.169		2.049		2.296		1.977		1.999	
Akaike info criterion	-1.788		-1.480		-1.513		-2.136		-1.762		-2.073		-2.029		-1.970		-1.854		-1.969	

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Schwarz criterion	-1.499	-1.191	-1.223	-1.847	-1.473	-1.783	-1.739	-1.681	-1.565	-1.680
Hannan-Quinn criter.	-1.673	-1.366	-1.398	-2.021	-1.647	-1.958	-1.914	-1.855	-1.739	-1.854

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Table 3(d) GARCH (1, 1) Model for portfolio Returns

Variable	P31		P32		P33		P34		P35		P36		P37		P38		P39		P40	
	c	p	c	p	c	p	c	p	c	p	c	p	c	p	c	P	c	p	c	p
Mean Equation																				
C	0.011	0.321	-0.013	0.228	-0.001	0.942	0.009	0.331	0.010	0.384	0.007	0.525	0.008	0.484	0.002	0.914	0.006	0.740	0.022	0.088
P1(-1)	0.431	0.000	0.293	0.017	0.067	0.765	0.262	0.028	0.147	0.138	0.259	0.081	0.297	0.021	0.102	0.315	0.064	0.537	0.260	0.044
Variance Equation																				
C	0.002	0.225	0.001	0.266	0.007	0.079	0.001	0.154	0.002	0.206	0.001	0.264	0.003	0.018	0.002	0.157	0.004	0.000	0.003	0.145
RESID(-1)^2	0.247	0.225	0.145	0.052	0.109	0.443	0.282	0.105	0.109	0.321	0.102	0.248	0.333	0.104	0.145	0.064	0.123	0.156	0.222	0.269
GARCH(-1)	0.530	0.091	0.775	0.000	0.561	0.052	0.547	0.005	0.570	0.099	0.748	0.000	0.369	0.105	0.561	0.000	0.535	0.000	0.456	0.209
RM_RF(α)	-0.013	0.598	-0.014	0.451	-0.015	0.760	-0.013	0.151	0.001	0.939	-0.009	0.537	-0.022	0.228	-0.009	0.413	-0.008	0.729	-0.020	0.316
SMB(ω)	0.051	0.151	0.017	0.587	-0.099	0.141	0.025	0.225	-0.019	0.487	0.002	0.936	0.017	0.473	0.043	0.034	-0.002	0.972	0.010	0.565
HML(γ)	-0.016	0.550	0.006	0.800	-0.016	0.815	-0.017	0.206	-0.031	0.097	-0.007	0.645	-0.014	0.538	-0.039	0.072	-0.035	0.515	-0.025	0.458
LIQUIDITY(π)	0.012	0.643	0.061	0.023	0.054	0.201	-0.054	0.080	-0.047	0.138	0.021	0.530	-0.074	0.024	-0.061	0.218	-0.136	0.084	-0.071	0.010
Diagnostic Test																				
R-squared	0.071		0.038		0.017		0.073		0.008		0.022		0.017		0.026		0.001		-0.054	
Log likelihood	80.498		77.698		69.093		86.021		75.162		80.328		75.470		69.628		59.969		77.025	
Durbin-Watson stat	2.282		2.135		1.787		1.964		1.936		2.093		2.204		1.824		1.971		2.112	
Akaike info criterion	-2.043		-1.963		-1.717		-2.201		-1.890		-2.038		-1.899		-1.732		-1.456		-1.944	
Schwarz criterion	-1.754		-1.674		-1.428		-1.912		-1.601		-1.749		-1.610		-1.443		-1.167		-1.654	
Hannan-Quinn criter.	-1.928		-1.848		-1.602		-2.086		-1.776		-1.923		-1.784		-1.617		-1.341		-1.829	

Table 3(e) GARCH (1, 1) Model for portfolio Returns

Variable	**P41**		**P42**		**P43**		**P44**		**P45**	
	c	**P**	**c**	**p**	**c**	**p**	**c**	**p**	**c**	**P**
Mean Equation										
C	0.006	0.536	0.025	0.059	0.020	0.000	0.011	0.344	0.022	0.109
P1(-1)	0.376	0.000	0.273	0.038	-0.057	0.742	0.309	0.020	0.204	0.106
Variance Equation										
C	0.003	0.034	0.002	0.000	0.002	0.125	0.002	0.288	0.003	0.101
RESID(-1)^2	0.532	0.077	0.252	0.242	0.203	0.180	0.207	0.296	0.162	0.095
GARCH(-1)	0.221	0.323	0.602	0.000	0.602	0.003	0.559	0.081	0.570	0.006
RM_RF(α)	-0.024	0.081	-0.015	0.613	0.001	0.974	-0.014	0.644	-0.011	0.526
SMB(ω)	-0.001	0.983	0.044	0.268	0.009	0.706	0.033	0.451	0.042	0.091
HML(γ)	0.004	0.284	-0.046	0.413	-0.058	0.094	-0.017	0.656	-0.046	0.104
LIQUIDITY(π)	-0.050	0.171	-0.176	0.185	-0.095	0.029	-0.005	0.938	-0.079	0.233
Diagnostic Test										
R-squared	-0.024		-0.023		-0.049		0.016		0.016	
Log likelihood	70.523		64.557		70.073		66.116		77.726	
Durbin-Watson stat	2.390		2.117		1.640		2.245		1.883	
Akaike info criterion	-1.758		-1.587		-1.745		-1.632		-1.964	
Schwarz criterion	-1.469		-1.298		-1.456		-1.343		-1.675	
Hannan-Quinn criter.	-1.643		-1.473		-1.630		-1.517		-1.849	

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Results:

The sum of δj and βi for P41 to P45 individually was less than 1 which proposes that shocks to the conditional variance will be highly persistent and model was valid. So, it denotes that the effect of present shocks remains in the forecast of variance for many periods in the future.

Now collectively looking at the diagnostic test values, the first parameter was R^2 which shows the goodness of model, in other words the percentage of the variance in the dependent variable that can be predicted from the independent variable (Liu and Brorsen, 1995). The highest value of the R^2 0.0734 (73.4%) of P34, the independent variables can predict the variance in the dependent variable. Whereas the lowest value of R^2 was -0.0723 (- 72%) for P22, which means that the model presents more unpredictability than the sample mean of the original time series. The log-likelihood value of a GARCH model shows the goodness of fit for a model. The higher the value of the log-likelihood, the superior a model fits a dataset. The log-likelihood value can vary from negative infinity to positive infinity for a given model. For this model the lowest values was 51.11 for P18, whereas the highest value for Log-l was 91.78 for P5.

The Durbin-Watson statistic is used to examine the autocorrelation of the outputs of a GARCH model. In the DW statistic, which ranges from zero to four, zero autocorrelation is represented by a value of 2.0. Values below 2.0 convey positive autocorrelation, whereas values above 2.0 demonstrate negative autocorrelation (Singh et al., 2016). On the other hand, the 21 portfolios display values over 2, with the P25 exhibiting the maximum value of 2.54, while the P43 has the lowest value of 1.6, indicating positive autocorrelation.

An additional statistical instrument to assess how successfully a model exposes the data it is based on is the Akaike information criterion (AIC). Statistically, models can be analysed using AIC to determine which model corresponds to the data (Cavanaugh and Neath, 2019). In this study, the highest value of AIC was -1.203 of P18 and lowest one was also negative -2.37 of P5. In this model the lowest the value the better fit the model. Schwarz criterion with the lowest value shows the best. This criterion considers both the amount of parameters the model uses and how closely the points fit the model. In this case the lowest value -2.08 and the highest -0.914, so this diagnostic criterion also shows the model was best-fit model for the portfolio returns volatility prediction.

Conclusion

As this research has the main focus to fill the gap it addressed, it is reasoned that the Fama-French model does adequately explain and forecast the performance of investments in Pakistan. The intercepts of the SMB and HML components used to evaluate the performance of Pakistani equity funds, however, are largely significant. This indicates that the size and value factors are powerful enough to explain the data. Since the coefficients are the most significant part of the model, the results provided by the study are considerable for the market factor and the liquidity factor. The findings were satisfactory to support the challenging models and to deliver

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widespread empirical shreds of evidence to the most relevant asset pricing model for the Pakistani stock market.

The main problem that was investigated in this study is the additional function of volatility and liquidity through the Fama French model in the Pakistan Stock Exchange (PSX) and how volatility and liquidity influence expected return deviations. By practically implementing the regression analysis for four factors the results were satisfactory in explaining the relationship between all the dependent and independent factors. The results showed that the liquidity factors played a major role in the stock market and liquidity premium exists in Pakistan's equity market.

The developed markets have a large positive correlation, whereas the emerging and developed markets have a comparatively small link, according to correlation analysis. The value of the likelihood statistics ratio is big, implying that the GARCH (1, 1) model is a profitable depiction of the daily return array, which successfully and competently depicts the ordered dependency of volatility. The findings showed that the sum of GARCH (1, 1) constants for all equity profits is less than 1, which is a crucial condition for mean reversion. As the sum approaches 1, the mean reversion process slows down for all developing and developed stock markets (Ahmed et al., 2013).

The GARCH (1, 1) model's primary objective is to produce precise forecasts of future volatility. Improving modelling will increase the usefulness of stock price as a signal for the intrinsic worth of securities since better predictions lead to more accurate pricing models of financial assets for practitioners and researchers. As a consequence of modelling volatility, stock prices will become more valuable as a signal for the intrinsic value of securities given that better modelling yields better predictions, which in turn lead to more accurate pricing models of financial assets for traders and scholars.

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