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Delusion and Madness of the Crowds: Collective Perception in Pakistani Exchange Markets

Furqan Ullah
Furqan815@gmail.com
PhD. Scholar, Department of Management Sciences, Islamia College, Peshawar

Hamid Ullah
hamidullah@icp.edu.pk
Assistant professor, Department of Management Sciences, Islamia College, Peshawar

Shahid Jan
shahidjan@icp.edu.pk
Associate Professor, Department of Management Sciences, Islamia College, Peshawar

Muhammad Asif
asifbaloch@cusit.edu.pk
Associate Professor, Department of Management Sciences, City University of Science and IT, Peshawar

Faiza Mahreen
Faizakiemail@gmail.com
PhD Scholar, Department of Management Science, Qurtaba University of Science and IT, Peshawar

Abstract:
The current study attempts to examine the associationbetween collective perception and exchange rates in Pakistan. We argue that people search online for information on currency exchange rates,and this online searching activity is transformed into data that could reflect people's interest in a given currency.The current study used Google Trends data of seven pairs of currencies to account for the level of interest in these currencies in Pakistan. Pairs of currencies include United Arab Emirates Dirham, Saudi Arabian Riyal, US dollar, Kuwaiti dinar, Qatari riyal, Omani riyal, and Canadian dollar against Pakistani rupees. Currencies are selected based on the highest level of remittances received in these currencies. The study has utilized data from 2010 to 2019 and used vector-autoregressive models forestimations.The results showed a significant impact of the collective perception measured through google trends data on exchange rates in Pakistani exchange markets.The authors analyzed the Google trends search queries for only seven pairs of currencies against the exchange rate in Pakistan. To be safe in the current and future, Investors in foreign and local currency exchange markets can benefit from the findings of this study at large. So, we argue that investors seeking information on exchange rate trends in Pakistan could utilize Google Trends information to forecast the future and make decisions accordingly. Google is widely used globally and hence in Pakistan due to the emerging trends of

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heavily relying on google searches for so many reasons. More specifically, exchange rates are searched on google, and thus google trends show the trends per click. This study is the first to investigate the google trends search data associated with the exchange rates in Pakistani markets with a broader view of collection perception in Pakistan.

Keywords: Exchange rates, Collective perceptions, Google trends, Vector-Autoregression, web search, Wisdom of Crowds.

INTRODUCTION

In today's era, the internet has become very much instrumental in the everyday life of a single person. A significant population of the countries is using web searches for their decision-making. In addition, for this purpose, they typically use the Google platform whenever they need to search for buying, selling, and for any topic, they want(Vaughan, 2014). Using Google for purchasing airplane tickets, branded clothes, and even selling cars has become a top trend on the internet. Most people are now using Google before buying or selling their currencies and individual stocks for investment(D'Avanzo, Pilato, and Lytras, 2017). Meanwhile, we are not just tapping for the wisdom of a single expert over the Web;instead of searching for collective wisdom over different websites and finds results just matching your requested queries.

In the current study, the authors examine the association between the online search activity for a particular currency and its influence on the foreign currency exchange rates. The study's authors are particularly interested in ascertaining how people approach internet search platforms for their decision-making in investment and trading activities. Keeping in view the wide use of the internet for social and financial causes, everyone can perform their investment and trading activity over the internet as long as they have this internet facility on hand(Dilmaghani, 2019). Therefore, the authors determined to utilized Google Trends search interest data to analyze an influence on the currency exchange rates and to see that does Crowd perception has an effect on the currency exchange rates for the seven countries of United Arab Emirates, Saudi Arabia, United States of America, Kuwait, Qatar, Oman and Canada against the country of Pakistan. A sample Graph of the Google trend search queries is given as below;

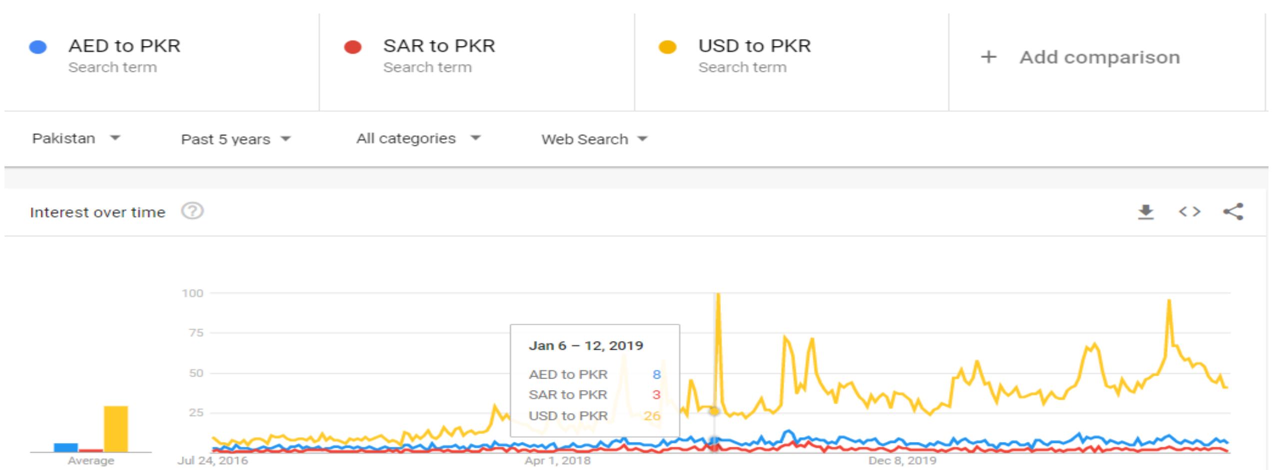

Figure 1: Google Trend Search Queries

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As for as the Google Trends literature is concerned, one may obtain information with Google Trends queries to predict trends in any economic, social, and political activities(Shang, Chen, and Livoti, 2017). Yet to know about the Google Trends search data, it is not that difficult to find the linkages with the exchange rate markets. The authors propose that the people's interest over Google for any currency can be used as a better proxy to predict the reaction of the exchange rates in the markets. The authors apply a multivariate data analysis approach of Vector Autoregression Models on seven currency pairs. The study's findings reveal the wisdom of the crowds' concept that there is a significant impact of overall collective perception on the respective exchange rates of the countries. Predictability of the Search Trends has become the subject matter for researchers over the last decade. This particular concept has exciting ramifications on how peoples make investment and trading decisions.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

The current study linksconcerning theoretical background stem from behavioral and neuroeconomics on a broader perspective and collective intelligence. The concept of behavioral economics keenly focuses on the idea that an individual's decision-making capacity is explained by cognitive insights that result in human behaviour. Searching on the Web is an application of behavioral economics by the end-users, as Preis, Moat, and Eugene Stanley (2013) and Choi and Varian (2012) discussed. Online web search is a particular behaviour that entails approximately 3 billion internet users worldwide, which provides an excellent platform to measure and collect the data concerning Collective Intelligence. Therefore, it is essential to know about the use and measurement of the people's collective intelligence, actions and the power of the web search to explain the influence of the online search through google trends on the exchange rate volatility in Pakistan. The debate of the Collective Intelligence discussed in the literature is provided in the Collective Intelligence section of the study. In this study, web search data is used as a measurement indicator for Collective Intelligence, presents the Web Search data, and provides details concerning Google Trend data and the literature conclusion at the end of this section.

Collective Actions and Intelligence (Madness and the Wisdom of Crowds)

Collective Intelligence occurs when groups of individuals collaborate in ways that seem intelligent, and the same issue has become a main long-standing interest of academics. Many can be wiser than the few reflects two conflicting views in the literature concerning collective intelligence. On the one hand, literature shows that some academics support the madness of crowds as, most of the time, human dynamics seem to be chaos, bubbles, and instability. On the other hand, the view of two heads is better than explains the phenomenon of the other people who support the idea of the wisdom of Crowds and clarify that the Crowd is always right and wiser than the single expert in the context whatever the case may be.

The book of Charles Mackay (2015) titled "Extraordinary Popular Delusions and the Madness of Crowds" is one of the earliest works delineating the subject of the wisdom of crowds or the madness of crowds. Mackay employs various examples to illustrate those collective human dynamics generate speculation,culminating in uncertainty and disorder. An in-depth analysis of online search trends provides insight into individual and collective search preferences, thus helping experts in defining and predicting market trends. This study aims at exploring individuals' interests in speculating currency exchange rates in pursuit of collective intelligence.

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This study's scope is limited and exclusively focused on exploring and evaluating mainstream online search trends. Mackay sheds light on agitation and chaos created by crowd mentality, which nurtures tendencies of arbitrage. Contrary to Mackay's perception of crowd madness, Surowiecki (2004) employed the expression "Wisdom of Crowds" to imply that the madness of the Crowd is undermined as Mackay predicted. Surowiecki debated whether group decision-making is more practical and valuable by the Crowd than individual expert opinion. Moreover, Surowiecki explored that Crowd collectively proves wiser, diverse, and leads to independent thought compared to the particular case. The study authors used web search-based Google Trend data to quantify the aggregate mechanism and use the Vector Autoregression (VAR) technique to investigate the people's perceptionof the respective exchange rates.

Many others in the literature (Kosonen, Gan, Vanhala, & Blomqvist, 2014; Garcia Martinez, 2015; Majchrzak & Malhotra, 2016; Kosonen, Gan, Olander, & Blomqvist, 2013; Brabham, 2012) argue about crowdsourcing, explaining that individuals and communities are keenly engaged for the solution of their problems. Keeping in view the use of Web Searches, crowds are included on individual and professional experts in their respective field of study and using the google searches to get information. During searching on the Web, they interact with intellectuals and filter for bad and good news in online communities. A debate of filtering online information by the collective and individual experts can be found (Reed, 2015).

The authors assume that individuals surfing online might be non-expert in searching currency exchange rates in this study. People searching for online currency exchange rates may be finance students, currency exchange traders, or occasional travelers. The authors assume that their interest in surfing foreign currency exchange rates is evidence of the minimum knowledge they have about the subject. Therefore, based on discussion, the authors can safely assume that crowds searching for and interested in the currency exchange rate are made up of experts in the case. Therefore, the authors expect to see the Crowd's wisdom in search of online currency exchange rates.

As a practice, Collective Intelligence is widely used in business, entertainment, science, and warfare-related activities. Therefore, to gain certain valuable information, people ask for help from the audience in the Crowd compared to an individual expert friend in the circle. Consequently, the audience seems to be correct by 91 percent of the time compared to only 65 percent of the expert friend (Bonabeau, 2009). The practice of collective wisdom of crowds has just turned out in profits for many industries and yet gained a lot of use.

Web Search Google Trend Data as a Proxy of Collective Intelligence

The new emergence of collaborative software and social networks has led to a change in investors' minds to solve complex problems and make investments. The authors of the study suggest postulating that a web-based internet tool gathers the data very smartly as Miner, (2005) reported the mechanism of Surowiecki (2004) pointed to turn the private judgment into a pearl of collective wisdom for decision making. Moreover, this mechanism provides a chance for researchers to research the concept of Collective Intelligence.

Single experts widely use web search datafor an ordinaryperson in various fields of research. Ettredge, Gerdes, and Karuga, (2005) suggested that using web search is fruitful to predict economic statistics, particularly for the unemployment rate in the country. Other researchers like

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Cooper, Mallon, Leadbetter, Pollack, and Peipins, (2005) use the web search data in the health sector to find the cancer disease for its health consequences. The authors believe that using the Web search data can also predict the market fluctuations while occurring any political or economic activity surrounding the country. Both studies provide positive results to use web search data to predict any of your interested topics.

Another study byHand and Judge, (2012) utilized the Google Trends search data to forecast the UK cinema admission while Goel, Hofman, Lahaie, Pennock, and Watts, (2010) predicted the volume of the sales of videos games, revenues for the film, and the rank of songs on the Billboard Hot 100 chart. Findingsof these studies showed that search counts are highly predictive of future outcomes. (2009) studied the sales of houses and predicted the future trend.

In the web search data, Google Trends is a powerful tool to predict any topic of your interest. It has gained much attention in forecasting the economic situation of the markets. D'Amuri and Marcucci, (2012), Fondeur and Karamé, (2013), Suhoy, (2009), and Askitas and Zimmermann, (2011) have investigated the unemployment rates using the web search data for the countries of Germany, France, United States, and Israel. The findings of these studies strongly support the use of Google Trends data which nicely improves the Unemployment rates compared to the other models employed to estimate the Unemployment rate. (2012b) also used Google Insights data to determine the unemployment rate, demand for Automobiles, vacation destination, and searched for the economic indicators in the study. Moreover, Google Trends data has been used by (Wu, 2013) to forecast future housing sales and prices in the markets of the United States of America. McLaren and Shanbhogue, (2012) have used the exact data for housing markets and labor forecasting.

Kristoufek, (2013) used a unique approach to study portfolio diversification using Google Trends data and said that the popularity of any given stock is associated with its riskiness.His study results revealed such a new technique to study portfolio diversification dominates the benchmarks method in the literature. And therefore, the authors believe that the same process may be used to study the Pakistani currency exchange rates markets by producing important results for the investors. Preis, Reith, and Stanley, (2010)examined whether people's interest in the internet search has any association with the financial market fluctuations and found strong evidence for the transactions in the S&P 100 index with that of each company search volume over the internet. That is why the study's authors found strong connections between the Google Trends search data and exchange rates in the market.

Research Hypotheses

$\boldsymbol{H_1}$**:**There is a positive and significant association between the exchange rate of *United Arab Emirates Dirham to Pakistan Rupee* and google trends search query of *United Arab Dirham to Pakistani Rupee.*

$\boldsymbol{H_2}$**:**There is a positive and significant association between the exchange rate of *Saudi Arabia Riyal to Pakistan Rupee* and google trends search query of *Saudi Arabia Riyal to Pakistani Rupee.*

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$\boldsymbol{H_3}$**:**There is a positive and significant association between the exchange rate of *United States Dollar to Pakistan Rupee* and google trends search query of *United States Dollar to Pakistani Rupee.*

$\boldsymbol{H_4}$**:**There is a positive and significant association between the exchange rate of *Kuwaiti Dinar to Pakistan Rupee* and google trends search query of *Kuwaiti Dinar to Pakistani Rupee.*

$\boldsymbol{H_5}$**:**There is a positive and significant association between the exchange rate of *Qatari Riyal to Pakistan Rupee* and google trends search query of *Qatari Riyal to Pakistani Rupee.*

$\boldsymbol{H_6}$**:**There is a positive and significant association between the exchange rate of *Omani Riyal to Pakistan Rupee* and google trends search query of *Omani Riyal to Pakistani Rupee.*

$\boldsymbol{H_7}$**:**There is a positive and significant association between the Canadian Dollar exchange rate *to Pakistani Rupee* and google trends search query of *Canadian Dollar to Pakistani Rupee.*

DATA AND RESEARCH METHODOLOGY

The Authors used the Google Trends search data and applieda Multivariate analysis approach by incorporating the reduced form of Vector AutoRegression, which is suitable to predict the exchange rates in the market.The authors collected the data from two reliable sources; people interest in exchange rates data were collected from the Google Trends website, while Treasury-bill rates, exchange rates were from the official website of State Bank of Pakistan. KSE-100 index is downloaded from the official website of the Pakistan Stock Exchange. All these data were downloaded for ten years, starting from Jan 2010 till the end of Feb 2020.

Based on remittances, the authors selected the following seven pairs of currencies looking into the volumes from the respective countries;

Table I.

Currencies and Foreign Remittances (Base Year 2010)

S.no	Country	Base Year	Remittances (in Million Dollars)
1.	UAE	2010	2038.52
2.	SAR	2010	1917.66
3.	USA	2010	1771.19
4.	Kuwait	2010	445.09
5.	Qatar	2010	354.15
6.	Oman	2010	287.27
7.	Canada	2010	115.12

The above table I shows the criteria that how the authors select countries (for their currencies exchange rates) against Pakistan. The authors choose counties based on the remittances received by the government of Pakistan, having the base year of 2010.

Table II.

Google Trend Search Queries

S.no	Currency Pair	Explanation of the pairs of currencies
1.	AED/PKR	United Arab Emirates Dirham to Pakistani Rupee

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2.	SAR/PKR	Saudi riyal to Pakistani Rupee
3.	USD/PKR	US dollar to Pakistani Rupee
4.	KWD/PKR	Kuwaiti dinar to Pakistani Rupee
5.	QAR/PKR	Qatari riyal to Pakistani Rupee
6.	OMR/PKR	Omani riyal to Pakistani Rupee
7.	CAD/PKR	Canadian Dollar to Pakistani Rupee

Table II shows the seven pairs of currencies used for Google Trends search Data regarding the people's interest in respective currencies. In the Google Trends search, AED/PKR query is used for the currency exchange rate of UAE to Pakistani Rupee, SAR/PKR for Saudi Arabia, USE/PKR for US Dollar, KWD/PKR for Kuwaiti Dinar, QAR/PKR for Qatari Riyal, OMR/PKR for Omani Riyal, and CAD/PKR for Canadian Dollar query into Pakistani Rupee.

EMPIRICAL RESULTS AND DISCUSSION

Descriptive statistics

Table III:

Descriptive Statistics of Google Trends Search Data

	A_P	S_P	U_P	K_P	Q_P	O_P	C_P
Mean	32.19672	28.29508	26.79508	18.94262	33.92623	27.76230	33.72951
Median	31.00000	28.50000	17.00000	21.00000	32.00000	30.00000	30.50000
Maximum	100.0000	100.0000	100.0000	55.00000	100.0000	100.0000	100.0000
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Std. Dev.	25.38029	22.24235	26.92473	11.87351	24.85567	19.89063	23.46477
Jarque-Bera	0.1240367	0.113037	0.312862	0.373435	0.6605176	0.191975	0.1055868
Probability	0.2026000	0.323511	0.512532	0.829678	0.3678801	0.711345	0.5096123
Observations	122	122	122	122	122	122	122

Above Table III shows descriptive statistics for Google Trends Search Data. A_P denotes the Google Trend Search Data of United Arab Emirates Currency against the Pakistani Rupee, S_P for Saudi Riyal, U-P for US dollar, K_P denotes Kuwaiti Dinar, Q_P for Qatari Riyal, O_P for Omani Riyal, and at last C_P stands for the Canadian Dollar against the Pakistani Rupee. For analysis, the authors used a total number of 122 observations in the study.

Table IV.

Descriptive Statistics of Exchange Rates

	ER_AP	ER_SP	ER_UP	ER_KP	ER_QP	ER_OP	ER_CP
Mean	28.84836	28.25000	105.9631	734.4131	61.50000	61.50000	61.50000
Median	28.00000	27.40000	102.8000	346.2000	61.50000	61.50000	61.50000
Maximum	43.40000	42.50000	159.3000	46014.40	122.0000	122.0000	122.0000
Minimum	22.90000	22.40000	84.00000	291.2000	1.000000	1.000000	1.000000
Std. Dev.	5.282424	5.175023	19.38857	4133.721	35.36241	35.36241	35.36241
Jarque-Bera	0.46842	0.471677	0.468201	0.719611	0.732196	0.732196	0.732196
Probability	0.601242	0.59110	0.601256	0.401641	0.257071	0.257071	0.257071
Observations	122	122	122	122	122	122	122

Above Table IV shows the Exchange rates descriptive statistics for the number of seven countries. In this table, ER_AP stands for Exchange rate of United Arab Emirates Dirham into Pakistani Rupee, ER_SP for Exchange rate of Saudi Arabian Riyal. Moreover, ER_UP for the exchange rate of US dollar, ER_KP for Kuwaiti Dinar, ER_QP for Qatari Riyal, ER_OP for

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Omani Riyal, and ER_CP denotes the exchange rate of one Canadian Dollar into Pakistani Rupee.

Vector-Autoregression (VAR) Model Results

This section discusses the results of the VAR model consisting ofthe independent variable of monthly Google Trends Search Data, the dependent variable of monthly average Exchange rates, control variables of Treasury Bills rates, and KSE-100 Index monthly data.

Table V:

Vector Autoregression Estimates for United Arab Emirates dirham

Date: 03/04/20 Time: 10:31
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_AP
A_P(-1)	0.014758 (0.00611) [2.41667]
ER_AP(-1)	1.437891 (0.09412) [15.2775]
ER_AP(-2)	0.737289 (0.14836) [4.96970]
ER_AP(-3)	0.271841 (0.09311) [2.91949]
TBR(-1)	0.305926 (0.10699) [2.85938]
TBR(-2)	0.526303 (0.16028) [3.28364]
TBR(-3)	0.244231 (0.11133) [2.19378]
KSE100(-2)	4.81123 (1.22334) [3.98236]
C	0.386475 (0.76539) [0.50494]
R-squared	0.355261
Adj. R-squared	0.350196
F-statistic	188.6077
Akaike AIC	6.401464
Schwarz SC	6.705065

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Mean dependent	32.89916
SD dependent	25.28529

The results of the Vector autoregressive model are reported in Table V. In this table, the dependent variable is the exchange rate of the United Arab Emirates Dirham to Pakistani Rupee (ER_AP), and the explanatory variables include google trend searching data of United Arab Emirates Dirham and its various lags. These results suggested that google trend data used to predict collective perception can forecast United Arab Emirates Dirham to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1st lag (A_P) has a significant and positive effect on the United Arab Emirates Dirham exchange rate. Moreover, the exchange rate results at 1st, 2nd, and 3rd lag are substantial, which shows that the prior month's exchange rates of United Arab Emirates Dirham can be used to forecast future exchange rates. The treasury bills rate also indicates that the monthly treasury bills rate at lag 1st, 2nd and 3rd also significantly affects the United Arab Emirates Dirham to Pakistani Rupee. Thus, one to three months' treasury bills rate positively and significantly affects the United Arab Emirates Dirham to Pakistani rupees. In terms of the KSE-100 index, the coefficient is significant at the 2nd lag on the United Arab Emirates Dirham exchange rate.

Table VI.

Vector Autoregression Estimates for Saudi Arabian Riyal

Date: 03/04/20 Time: 10:45
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments

	ER_SP
S_P(-3)	0.008959 (0.00435) [2.05851]
ER_SP(-1)	1.488210 (0.09128) [16.3036]
ER_SP(-2)	0.723885 (0.14812) [4.88721]
TBR(-1)	0.338238 (0.10400) [3.25215]
KSE100(-2)	3.341205 (3.32345) [1.02048]
C	-0.841784 (0.52179) [-1.61327]
R-squared	0.373736
Adj. R-squared	0.359442
F-statistic	61.12593

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Log-likelihood	-413.9894
Akaike AIC	7.176293
Schwarz SC	7.479894
Mean dependent	28.89076
SD dependent	22.17297

Above,Table VIreports the result of the vector Autoregression model. The dependent variable is Saudi Arabian Riyal to Pakistani Rupee (ER_SP), and the explanatory variables include google trend searching data of Saudi Arabian Riyal and its various lags. Results suggested that google trend data used to predict collective perception can forecastSaudi Arabian Riyal to Pakistani Rupee. Treasury bills rate and KSE-100 index are used as control variables and the lags of these variables. Empirical results showed that google trend search at 1st lag (S_P) has a significant and positive effect on the Saudi Arabian Riyal exchange rate.

Moreover, the exchange rate results at 1stand 2nd lags are significant, which shows that the prior month's exchange rates of Saudi Arabian Riyal can be used to forecast future exchange rates. The treasury bills rate also indicates that the monthly treasury bills rate at lag 1sthasa significant and positive effect on the Saudi Arabian Riyal to Pakistani Rupee. Thus, the previous one-month treasury bills rate positively and significantly affects the Saudi Arabian Riyal to Pakistani rupees. In terms of the KSE-100 index, the coefficient is significant at the 2nd lag on the Saudi Arabian Riyal exchange rate.

Table VII.

Vector Autoregression Estimates US Dollar

Date: 03/04/20 Time: 10:49
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_UP
U_P(-1)	0.256651 (0.01559) [16.46071]
ER_UP(-1)	1.465694 (0.09629) [15.2213]
ER_UP(-2)	0.730134 (0.15282) [4.77784]
ER_UP(-3)	0.222943 (0.09444) [2.36066]
TBR(-1)	1.157286 (0.40920) [2.82820]
TBR(-2)	2.144056 (0.60264) [3.55775]

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TBR(-3)	1.086234 (0.42183) [2.57507]
KSE100(-2)	0.000149 (0.00012) [1.23484]
C	2.359607 (2.56228) [0.92090]
R-squared	0.395332
Adj. R-squared	0.394804
F-statistic	1883.547
Log-likelihood	-201.4257
Akaike AIC	3.603794
Schwarz SC	3.907395
Mean dependent	106.5034
SD dependent	19.32623

The results of the Vector autoregressive model are reported in Table VII, where the dependent variable is the US dollar to Pakistani Rupee (ER_UP) while the explanatory variables include google trend searching data of US dollar and its various lags. These results revealed that google trend data used to predict collective perception has proved to be an excellent proxy to forecast the US dollar to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1st lag (U_P) has a highlysignificant and positive effect on the US dollar exchange rate. Moreover, the exchange rate results at 1st, 2nd, and 3rd lag are substantial, which shows that the prior month's exchange rates of the US dollar can be used to forecast future exchange rates. The treasury bills rate also indicates that the monthly treasury bills rate at 1st, 2nd and 3rdlags simultaneously significantly affects the US dollar to Pakistani Rupee. Thus, one to three months' treasury bills rate positively and substantially affects the US dollar to Pakistani rupees. In terms of the KSE-100 index, the coefficient is significant at 2nd lag on the US dollar exchange rate.

Table VIII.

Vector Autoregression Estimates for Kuwaiti Dinar

Date: 03/04/20 Time: 10:51
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_KP
K_P (-1)	50.47275 (49.4508) [1.02067]
ER_KP (-1)	0.021094 (0.009089) [2.32091]
KSE100(-1)	-0.238262 (0.24912) [-0.95643]

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TBR(-2)	5832.563 (1688.86) [3.45355]
TBR(-3)	4615.027 (1156.23) [3.99143]
C	-4139.125 (4052.94) [-1.02127]
R-squared	0.211919
Adj. R-squared	0.122702
F-statistic	2.375326
Log-likelihood	-1146.563
Akaike AIC	19.48845
Schwarz SC	19.79206
Mean dependent	745.5244
SD dependent	4185.333

The results of the Vector autoregressive model are reported in Table VIII, where the dependent variable is Kuwaiti dinar to Pakistani Rupee (ER_KP), and the explanatory variables include google trend searching data of Kuwaiti dinar and its various lags. These results suggested that google trend data used to predict collective perception can forecast Kuwaiti dinar to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1st lag (K_P) has a significant and positive effect on the Kuwaiti dinar exchange rate. Moreover, the exchange rate results at only 1st lag are significant,which shows that the prior one-month exchange rates of Kuwaiti dinar can be used to forecast future exchange rates. The treasury bills rate also indicates that the monthly treasury bills rate at lag 2nd and 3rd also significantly affects the Kuwaiti dinar to Pakistani Rupee. Thus, two to three months' treasury bills rate positively and substantially affects the Kuwaiti dinar to Pakistani rupees. In terms of the KSE-100 index, the coefficient is significant at the 1st lag on the Kuwaiti dinar exchange rate.

Table IX.

Vector Autoregression Estimates for Qatari Riyal

Date: 03/04/20 Time: 10:57
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_QP
Q_P(-1)	0.160362 (0.06538) [2.45259]
ER_QP (-1)	0.731489 (0.09470) [7.72440]
TBR(-3)	0.439237 (3.57426)

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	[0.12289]
KSE100(-2)	0.013081
	(0.00105)
	[12.4724]
C	-2.026184
	(12.9976)
	[-0.15589]
R-squared	0.890436
Adj. R-squared	0.878032
Sum sq. resids	15385.04
S.E. equation	12.04748
F-statistic	71.78892
Log-likelihood	-458.1443
Akaike AIC	7.918392
Schwarz SC	8.221994
Mean dependent	60.00000
SD dependent	34.49638

Table IXshows the VAR estimation result of QAR/PKR. The dependent variable is Qatari Riyal to Pakistani Rupee (ER_QP), and the explanatory variables include google trend searching data of Qatari Riyal and its various lags. These results suggested that google trend data used to predict collective perception can forecast Qatari Riyal to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1^{st} lag (Q_P) has a significant and positive effect on the Qatari Riyal exchange rate.

Moreover, the exchange rate results at 1^{st} lag are significant, which shows that prior only one-month exchange rate of Qatari Riyal can be used to forecast future exchange rates. The treasury bills rate has no longer effectively predicted the exchange rate of Qatari Riyal into Pakistan rupee. In terms of the KSE-100 index, the coefficient is significant at the 2^{nd} lag on the Qatari Riyal exchange rate.

Table X.

Vector Autoregression Estimates for Omani Riyal

Date: 03/04/20 Time: 10:59
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_OP
O_P(-1)	0.086581
	(0.00903)
	[14.6671]
ER_OP (-1)	1.125330
	(0.09912)
	[11.3535]
TBR(-3)	0.347212
	(1.81681)
	[0.19111]

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KSE100(-1)	-0.000448 (0.00038) [-1.18344]
KSE100(-3)	1.671205 (0.00037) [45.3404]
C	0.675540 (6.27447) [0.10766]
R-squared	0.372628
Adj. R-squared	0.369529
F-statistic	313.8792
Log likelihood	-375.9202
Akaike AIC	6.536474
Schwarz SC	6.840076
Mean dependent	62.94958
SD dependent	34.58393

Above Table X shows the result of the vector Autoregression Estimates for Omani Riyal. The dependent variable is Omani Riyal to Pakistani Rupee (ER_OP), and the explanatory variables include google trend searching data of Omani Riyal and its various lags. These results suggested that google trend data, which can predict collective perception, can forecast Omani Riyal to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1st lag (O_P) has a significant and positive effect on the Omani Riyal exchange rate. Moreover, the exchange rate results at the 1st lag are substantial, which shows that prior only one-monthexchange rate of Omani Riyal can be used to forecast future exchange rates. In terms of the KSE-100 index, the coefficient is significant at 1stand 2nd lags on the Omani Riyal exchange rate.

Table XI.

Vector Autoregression Estimates for the Canadian Dollar

Date: 03/04/20 Time: 11:03
Sample (adjusted): 2010M04 2020M02
Included observations: 119 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	ER_CP
C_P(-1)	-0.447567 (0.20289) [-2.20597]
ER_CP (-1)	0.855648 (0.09615) [8.89866]
KSE100(-2)	0.020571 (0.00169) [12.2088]
TBR(-1)	0.848881 (0.055959) [15.17012]

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C	23.91262 (21.2881) [1.12328]
R-squared	0.740298
Adj. R-squared	0.710898
F-statistic	25.18004
Log-likelihood	-513.5920
Akaike AIC	8.850286
Schwarz SC	9.153888
Mean dependent	61.90756
SD dependent	35.70500

Table XI shows the Vector Autoregression Estimates for the Pair of Canadian Dollar into Pakistani Rupee. The dependent variable is Canadian Dollar to Pakistani Rupee (ER_CP), and the explanatory variables include google trend searching data of Canadian Dollar and its various lags. These results suggested that google trend data, which can predict collective perception, can forecast the Canadian Dollar to Pakistani Rupee. The control variables include the Treasure bills rate and KSE-100 index and their lags. The results showed that google trend search at 1st lag (C_P) has a significant and positive effect on the Canadian dollar exchange rate.

Moreover, the exchange rate at the 1st lag is significant, which shows that prior only one-month exchange rates of the Canadian Dollar can be used to forecast future exchange rates. The treasury bills rate also indicates that the monthly treasury bills rate at lag 1sthasa significant and positive effect on the Canadian Dollar to Pakistani Rupee. Thus, only a one-monthTreasury bills rate positively and significantly affects the Canadian Dollar to Pakistani rupees. In terms of the KSE-100 index, the coefficient is significant at 2nd lag on the Canadian dollar exchange rate.

Suggestions and Conclusion

Based on the empirical results, analysis, and discussion, the author's research suggests that people usually search online for currency exchange rates. Therefore, this process of seeking information over the Web can be translated into the data on people's interest for a given pair of currencies. In this study, the authors employed Google Trends online Search data to capture the optimal level of interest for the seven currency pairs: UAE dirham, Saudi Arabian riyal, US dollar, Kuwaiti dinar, Qatari riyal, Omani riyal, and Canadian Dollar. The author used the multivariate data analysis approach in the context of vector Autoregression models. The authors estimated all the possible subset models and properly incorporated seven models based on AIC, SC, and Adjusted R^2.

Therefore, the authors believe that Google Trends search data proved an excellent tool for investors to forecast future exchange rates. Hence, the authors illustrate people's level of interest can be used to strengthen the prediction level of the currency exchange rate by the investors in the exchange markets. The study results align with the outcome of(Reed and Ankouri, 2019) and (Choi and Varian, 2012a). Future researchers can carry out the same study by finding out the predictive power of Google Trends Search data against cross-country currency exchange rates.

Limitations and Future Directions

This study has several limitations. First, this study has examined only seven pairs of currencies, i.e., Dirham, Riyal, US Dollar, Kuwaiti Dinar, Qatari Riyal, Omani Riyal, and Canadian Dollar

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against the currency of Pakistan. Second, the data concerning exchange rates are collected for the year 2019. Future researchers can carry out the same study by finding out the predictive power of Google Trends Search data against cross-country currency exchange rates. Third, this research can be extended to analyze theexisting variables google trends and exchange rates in the context of Covid-19 Global pandemic disease and Geert Hofstede national cultural dimensions.

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Competing Interest

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

This research was jointly conceptualized, and all the authors, Furqan Ullah, Hamid Ullah, Shahid Jan, Muhammad Asif, and Faiza Mahreenequally contributed to this work.

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Data availability

The authors confirm that the data supporting the findings of this study are available within the article.

Disclaimer

The views expressed in the article are those of the authors and do not necessarily reflect the official policy or position of the institution to which they are affiliated.

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