EXCHANGE RATE RETURNS

IEOR E4150

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Dataset

The dataset consists of the daily exchange rates denominated in USD, and monthly geopolitical risk (GPR) index of 10 countries, from January 1, 2005, to November 3, 2022. The daily data are resampled to represent monthly data. A total of 4647 daily data points were collected from Yahoo Finance and 213 monthly data points were collected from Caldara and Iacoviello (2018) for each exchange rate. The countries and exchange rates selected are Argentina (ARG), Australia (AUD), Brazil (BRL), Canada (CAD), Switzerland (CHF), Chile (CLP), China (CNY), Colombia (COP), Denmark (DKK), Egypt (EGP), United Kingdom (GBP), Hong Kong (HKD), Hungary (HUF), Indonesia (IDR), Israel (ILS), India (INR), Japan (JPY), Korea (KRW), Mexico (MXN), Malaysia (MYR), Norway (NOK), Peru (PEN), Philippines (PHP), Poland (PLN), Russia (RUB), Saudi Arabia (SAR), Sweden (SEK), Thailand (THB), Tunisia (TND), Turkey (TRY), Taiwan (TWD), Ukraine (UAH), Venezuela (VEF), South Africa (ZAR). Besides, we collected 214 monthly interest rate data from OECD, which supports the later section of our project.

Project Goals

Foreign exchange is a dynamic trading market. Analyzing and predicting the exchange rate returns not only assists trading strategy formulation process, but also provides an in-dept knowledge of the economies. Geopolitical risk has been studied in correlations with exchange rate returns (Iyke et al., 2022), suggesting intriguing topic questions of whether the Russia-Ukraine war leads to currency asymmetries, whether terrorist attacks matter for currency excess returns, or finding the optimal portfolios of national currencies during the Russian-Ukrainian Conflict, etc.

For a single exchange rate, by employing the techniques of statistical analysis, we examine the distribution of exchange rate returns by fitting a normal distribution. Even if the previous statistical test criteria are not satisfied, we still perform the remaining tests, including a first-order autoregression of returns. By observing the exchange rate performance over time, we could identify any positive or negative trends in its log-return, possibly suggesting the depreciation or appreciation of the currencies, and in general, exhibiting problems of the global forex market, such as worldwide inflation.

For pairs of exchange rates, we conduct the tests for equal means, accordingly, perform the regression of one return on the other. The results could show which pairs of currencies are correlated and tend to move in similar patterns.

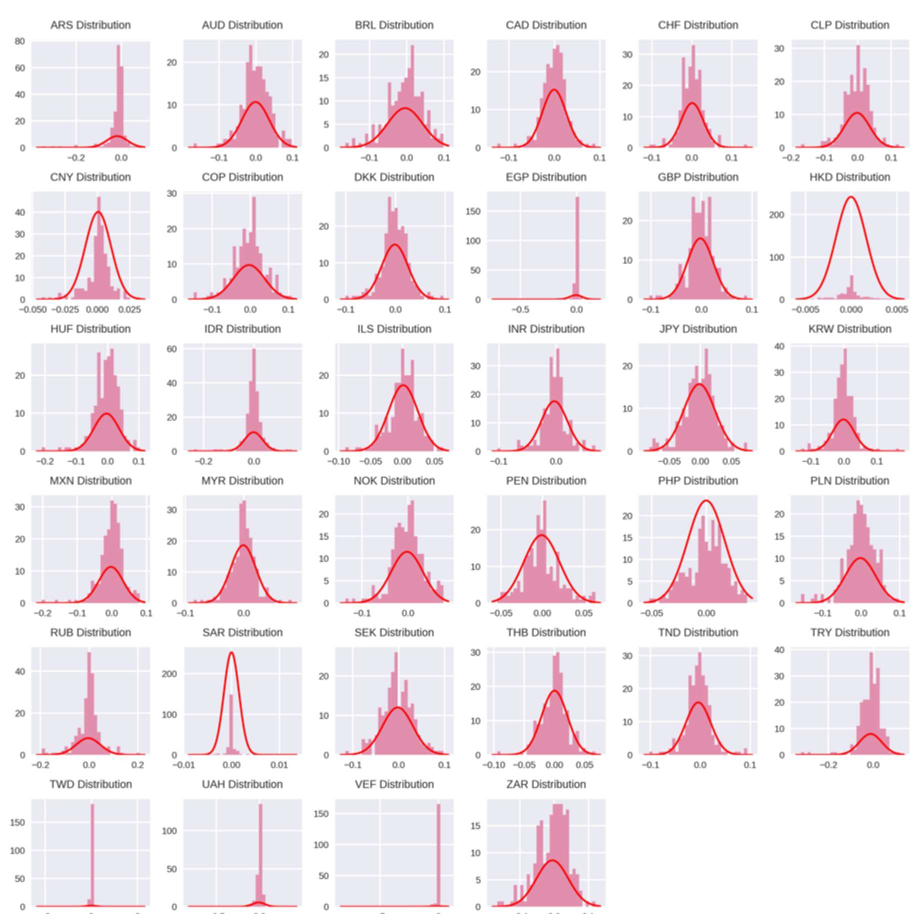
Lastly, testing whether the GPR index has influence on the exchange rate return. All the regressions in this project could somewhat assist in exchange rate prediction, which is an essential but challenging task in both finance and economics and still debated in random walk theory.

Table 1. Descriptive Statistics

Log-returns	Obs.	Mean	SD	Skew.	Kurt.	AR(1) β_0	AR(1) β_1	AR(1) R^2
ARS	213	-0.019	0.046	-4.288	24.022	-0.018	0.071	0.005
AUD	197	-0.001	0.037	-0.459	1.863	-0.001	-0.004	0.0
BRL	199	-0.004	0.047	-0.508	0.599	-0.005	0.01	0.0
CAD	213	-0.0	0.026	-0.419	2.699	-0.001	-0.084	0.007
CHF	213	0.001	0.028	0.226	3.647	0.001	-0.167	0.028
CLP	213	-0.002	0.038	-0.512	1.976	-0.003	-0.124	0.015
CNY	213	0.001	0.01	-1.051	3.637	0.0	0.335	0.11
COP	213	-0.003	0.041	-0.355	0.965	-0.004	-0.041	0.002
DKK	213	-0.001	0.027	-0.265	2.047	-0.001	-0.02	0.0
EGP	213	-0.007	0.055	-10.187	128.588	-0.007	-0.042	0.002
GBP	213	-0.002	0.026	-0.332	1.668	-0.002	0.04	0.002
HKD	213	-0.0	0.002	0.183	1.947	-0.0	-0.105	0.011
HUF	213	-0.004	0.04	-1.039	3.863	-0.004	-0.002	0.0
IDR	213	-0.002	0.036	-1.468	13.017	-0.003	-0.121	0.015
ILS	213	0.001	0.023	-0.576	1.275	0.001	-0.015	0.0
INR	213	-0.003	0.023	-0.466	2.762	-0.003	0.048	0.002
JPY	213	-0.002	0.025	-0.392	1.088	-0.001	0.094	0.009
KRW	213	-0.002	0.033	0.060	4.906	-0.002	-0.117	0.014
MXN	213	-0.003	0.035	-1.421	6.148	-0.003	0.006	0.0
MYR	213	-0.001	0.021	-0.225	2.370	-0.001	0.006	0.0
NOK	213	-0.002	0.035	-0.410	1.210	-0.002	-0.022	0.0
PEN	213	-0.001	0.022	0.372	0.754	-0.001	-0.168	0.028
PHP	213	-0.0	0.017	-0.395	0.013	-0.0	0.066	0.004
PLN	213	-0.002	0.04	-0.814	2.036	-0.002	0.037	0.001
RUB	213	-0.004	0.05	-0.505	4.239	-0.003	0.155	0.024
SAR	213	-0.0	0.002	1.943	24.181	-0.0	-0.353	0.124
SEK	213	-0.002	0.033	-0.025	0.588	-0.002	-0.013	0.0
THB	213	0.0	0.021	-0.282	1.600	0.0	-0.054	0.003
TND	213	-0.004	0.025	0.158	3.061	-0.005	-0.07	0.005
TRY	213	-0.012	0.05	-2.152	10.810	-0.011	0.104	0.011
TWD	197	-0.0	0.215	-0.315	96.994	0.0	-0.5	0.25
UAH	213	-0.009	0.072	-5.481	62.088	-0.011	-0.206	0.042
VEF	177	-0.066	0.607	-12.691	165.801	-0.062	0.06	0.004
ZAR	213	-0.005	0.047	-0.525	0.458	-0.005	-0.073	0.005

This table reports the selective descriptive statistics for monthly exchange rate log returns $\left(\mathrm{EXR}_t = \ln \frac{\mathrm{EX}_t}{\mathrm{EX}_{t-1}}\right)$ where EX_t is the exchange rate at time t for 34 countries. The statistics include the mean, standard deviation (SD), Skewness (Skew.), Kurtosis (Kurt.). AR(1) refers to the autoregression of order 1.

Figure 1. Histogram with fitted normal distribution



Analysis

Single Exchange Rate Analysis

First, we test the assumption that every monthly exchange rate return data comes from a normal distribution. Table 1 shows the data statistics, from which we estimate that the exchange rate returns are mainly negatively skewed and heavy-tailed with negative mean, slightly below zero. The histograms and fitted normal distribution plotted in Figure 1 also shows the similar assertion. Besides, some of the distributions is supposed to have super heavy tails and tall peaks including ARS, EGP, IDR, SAR, TRY, TWD, UAH and VEF.

Table 2. 95% Confidence Interval

Index	95% CI for Mean	95% CI for Variance
ARS	(-0.021607, -0.015761)	(0.008943, 0.023818)
AUD	(-0.00319, 0.001545)	(0.005868, 0.015628)
BRL	(-0.007471, -0.001495)	(0.009349, 0.024898)
CAD	(-0.002093, 0.001221)	(0.002874, 0.007654)
CHF	(-0.000937, 0.002587)	(0.003249, 0.008652)
CLP	(-0.00467, 0.000139)	(0.006053, 0.016119)
CNY	(-0.000014, 0.001245)	(0.000415, 0.001105)
COP	(-0.005959, -0.000764)	(0.007065, 0.018815)
DKK	(-0.002959, 0.000412)	(0.002974, 0.00792)
EGP	(-0.009955, -0.003054)	(0.012462, 0.033189)
GBP	(-0.00391, -0.000648)	(0.002785, 0.007417)
HKD	(-0.000135, 0.000073)	(0.000011, 0.00003)
HUF	(-0.006245, -0.001148)	(0.006798, 0.018105)
IDR	(-0.004753, -0.000218)	(0.005383, 0.014336)
ILS	(-0.000447, 0.002458)	(0.002209, 0.005883)
INR	(-0.004411, -0.001535)	(0.002164, 0.005764)
JPY	(-0.003277, -0.00006)	(0.002709, 0.007214)
KRW	(-0.003621, 0.000553)	(0.00456, 0.012144)
MXN	(-0.004935, -0.000463)	(0.005235, 0.013943)
MYR	(-0.002376, 0.000337)	(0.001926, 0.005128)
NOK	(-0.004468, -0.000077)	(0.005047, 0.013441)
PEN	(-0.002302, 0.000425)	(0.001945, 0.005181)
PHP	(-0.001289, 0.000864)	(0.001213, 0.003232)
PLN	(-0.004481, 0.000531)	(0.006576, 0.017512)
RUB	(-0.006842, -0.000506)	(0.010507, 0.027981)
SAR	(-0.000107, 0.000093)	(0.00001, 0.000028)
SEK	(-0.004221, -0.000023)	(0.004613, 0.012285)
THB	(-0.001265, 0.001426)	(0.001894, 0.005044)
TND	(-0.005631, -0.002444)	(0.002658, 0.007078)
TRY	(-0.015534, -0.009208)	(0.010476, 0.027901)
TWD	(-0.013627, 0.013602)	(0.194039, 0.516764)
UAH	(-0.013789, -0.004742)	(0.02142, 0.057047)
VEF	(-0.104268, -0.027513)	(1.541814, 4.10616)
ZAR	(-0.008157, -0.002271)	(0.009067, 0.024147)

To further improve the statistics, we construct confidence intervals for the exchange rate returns mean and variance by utilizing the t-distribution with $n-1$ degree of freedom for the mean tests, and the chi-squared distribution with $n-1$ degree of freedom for the variance tests in table 2.

The 95% confidence interval for mean and variance are small and close to zero, with the upper bound and lower bound not exceeding ± 0.01, except for TWD, VEF and UAH with considerably large confidence interval for variance. For HKD and SAR, the confidence interval for variance is extremely small, implying little variability among the data.

After examining the distribution and properties of the exchange rate returns, we then perform a linear regression of the monthly log-returns against time. The model takes the form of simple linear regression:

$$\mathrm{EX}R_t = \beta_0 + \beta_1 \mathrm{EX}R_{t-1} + \epsilon_t$$

The results are shown in the three last columns of Table 1. Only for CNY and TWD, R_2 is above 0.10, and for the rest of the exchange rates, R_2 is approximately zero, implying that the exchange rate returns of the previous month might not explain much of the current month's returns. To further understand, we illustrate the data on the scatter plots with regression line (Figure 2), and the residual plots (Figure 3). None of the scatter plots indicate a linear pattern, and the residuals also seem non-linear. From the above analysis, we roughly conclude that a simple linear regression technique cannot be implemented to estimate the exchange rate returns, due to the lack of explanation in the volatility of the data. However, if we still believe in the predictivity of a linear model, we could conduct multiple linear regressions, taking more time-steps into accounts, for example, an autoregressive model using the input exchange rate returns of the last k months, with k being a hyperparameters that we could tune to obtain optimal performance. This report shows the initial results using simple linear regression. The idea of using available historical timeseries data to predict the future return in the market can be expanded to many techniques, from traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA), to complex deep learning algorithms such as Long Short-Term Memory (LSTM).

Figure 2. Scatter plots with linear regression lines (AR(1))

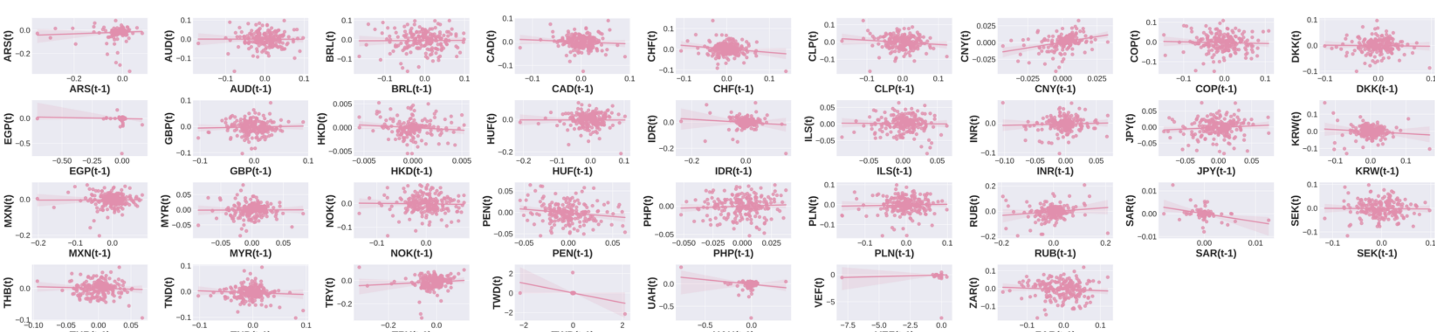
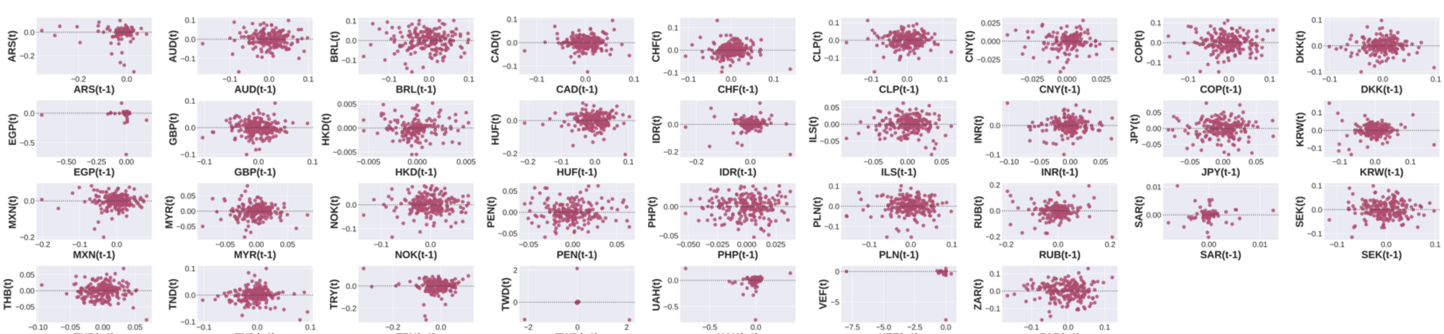


Figure 3. Graphical depiction of the residuals (AR(1))



Two Exchange Rates Analysis

In this section, we will consider conducting the t-test for two sample means. We first compute the correlation matrix between the analyzed exchange rate returns to see if they are close to zero, then we could decide whether to use the t-test for matched-paired samples, or the t-test for independent samples. The results show that the correlations between the returns are quite large, so the t-test for paired-sample mean with $n-1$ degree of freedom should be employed.

Due to the restriction of report, we only exhibit the exchange rate returns analysis between ARS and the other thirty-three exchange rates. The null hypothesis is formulated as the mean return of ARS and the mean return of the other exchange rate in the pair are equal, the alternative hypothesis is their mean returns are different. The result of the tests is reported in the first three columns of Table 3.

Except for TRY, TWD and VEF, the p-value from the t test for the means of paired samples are below 0.01, thus we can reject the null hypothesis at 1% level of significance for 30/33 (91%) of the data. We could say that the means of ARS return and other exchange rates' returns are statistically significantly different.

A simple linear regression is performed on each of exchange rates' returns on ARS's return, the coefficients are also estimated and reported in table 3. All the slope coefficients of the models have t-test greater than critical values of $t_{0.01}$, so we could reject the null hypothesis that the true $\beta_1 = 0$ at 1% level of significance. The only regression that has a significantly large R^2 is the regression of TRY on ARS returns, whose R^2 is approximately 0.15. The other exchange rates seem to have no significantly large influence on ARS.

Table 3. T-test for mean difference and Linear Regression of the other log-return on the return of ARS.

Index	Corr.	t	p-value	Linear Regression			
				β_0	β_1	t	R^2
AUD	0.099	4.646	6E-06	-0.0198	0.1258	-5.84	0.0097
BRL	0.293	3.815	0.00018	-0.0184	0.2951	-5.671	0.0861
CAD	0.155	5.378	0	-0.0186	0.2727	-5.914	0.0239
CHF	-0.034	5.194	0	-0.0186	-0.0567	-5.867	0.0012
CLP	0.147	4.326	2.3E-05	-0.0183	0.1792	-5.806	0.0217
CNY	0.271	6.315	0	-0.0195	1.2579	-6.35	0.0734
COP	0.17	3.963	0.0001	-0.018	0.1911	-5.743	0.0289
DKK	0.059	4.885	2E-06	-0.0186	0.1024	-5.843	0.0035
EGP	0.043	2.539	0.01185	-0.0184	0.0366	-5.77	0.0019
GBP	0.12	4.77	3E-06	-0.0182	0.2156	-5.746	0.0145
HKD	0.078	5.898	0	-0.0186	2.186	-5.876	0.0061
HUF	0.13	3.819	0.00018	-0.0181	0.1496	-5.732	0.017
IDR	0.11	4.271	2.9E-05	-0.0183	0.1415	-5.791	0.012
ILS	0.075	5.736	0	-0.0188	0.15	-5.939	0.0056
INR	0.174	4.790	3E-06	-0.0176	0.3543	-5.588	0.0304
JPY	-0.064	4.580	8E-06	-0.0189	-0.1169	-5.942	0.0041
KRW	0.116	4.668	5E-06	-0.0184	0.1628	-5.836	0.0135
MXN	0.216	4.502	1.1E-05	-0.0179	0.2825	-5.761	0.0467
MYR	0.18	5.443	0	-0.0183	0.3874	-5.845	0.0323
NOK	0.136	4.44	1.4E-05	-0.0183	0.181	-5.793	0.0185
PEN	0.167	5.432	0	-0.0183	0.3571	-5.852	0.0277
PHP	0.194	5.848	0	-0.0186	0.5256	-5.958	0.0375
PLN	0.108	4.235	3.4E-05	-0.0184	0.1261	-5.829	0.0117
RUB	0.192	3.57	0.00044	-0.018	0.1767	-5.768	0.0367
SAR	0.021	5.893	0	-0.0187	0.6032	-5.881	0.0004
SEK	0.082	4.418	1.6E-05	-0.0184	0.1136	-5.812	0.0067
THB	0.052	5.488	0	-0.0187	0.113	-5.892	0.0027
TND	0.028	4.105	5.8E-05	-0.0185	0.0508	-5.745	0.0008
TRY	0.382	1.718	0.08733	-0.0143	0.3529	-4.733	0.1459
TWD	0.039	1.277	0.20308	-0.0199	0.0087	-5.848	0.0015
UAH	0.059	1.658	0.09876	-0.0183	0.0383	-5.731	0.0035
VEF	0.025	-0.959	0.33891	-0.0219	0.0021	-5.796	0.0006
ZAR	0.278	3.524	0.00052	-0.0172	0.2758	-5.615	0.0771

This table reports the results of the t test for the mean of paired samples between ARS and the other exchange rates' returns, and the simple linear regression coefficients of other exchange rates' returns on the return of ARS. Correlation (Corr.), the statistics $t = \frac{\bar{d}}{s_d/\sqrt{n}}$ with $d_t = EXR_{X,t} - EXR_{ARS,t}$. The linear regression coefficients are estimated from the model $\mathrm{EXR}_{\mathrm{ARS},t} = \beta_0 + \beta_1 + \mathrm{EXR}_{\mathrm{X},t} + \epsilon$, with X being an exchange rate return other than ARS. t test in the linear regression is the test whether the slope coefficient $\beta_1 = 0$, and $R^2 = 1 - \frac{RSS}{TSS}$ is the coefficient of determination. (Review: RSS: sum of squared residual $\sum_i^n(\hat{y}_i - \bar{y})$, TSS: total sum of squares $\sum_i^n(y_i - \bar{y})$)

So far, we have statistically analyzed the exchange rate returns individually and pairwise. Based on the given information, we could draw some assertions about the economic effects of analyses. Firstly, in this project, we intentionally only select the exchange rates of the currencies that belong to one country, for example, EUR is excluded, so they are associated with the monetary policy as well as trading supplies and demands of a specific nation. Therefore, the exchange rate returns reflect the appreciation and depreciation of the national currencies. If an exchange rate return is negative over a period, meaning the national currency is depreciated compared with USD, it might suggest a sell signal for the forex investors, and if the negative period is long, it could reflect an economic distress, and the reversed scenario could be interpreted from the situation where an exchange rate return is positive over a period. If the long-term prediction of exchange rate return is of concern, a moving average line which dynamically illustrates the trend of the data is helpful, so we could ignore the extreme noises, which is a known feature of the daily exchange rate data.

If we continue performing a series of regression of one exchange rate return on the other, the results vary greatly. For instance, the return of ARS, CNY, EGY, HKD, JPY, SAR, TWD, UAH and VEF might not significantly be explained by other returns, but the regression of other returns on AUD, CAD, CHF, COP, DKK, GBP, etc. have significantly large R^2, some of which have R^2 over 0.70. This reflects the difference among the treatment of currencies, also the trading policies. By examining the degree of volatility and the correlations of the exchange rate return with others, we could roughly classify, or group the currencies depending on their slope coefficients and coefficients of determination. Some possible grouping suggestion is by geography: the exchange rate returns of Eastern Asian countries such as China, Hong Kong, Japan and Taiwan tend to behave more independently, whereas the exchange rate returns of European countries such as Switzerland, Norway, Turkey are somewhat more dependent on others, the reason could be that their economy are more closely tied together, as according to the data of the WTO, the EU-27 countries are – by some margin – the countries with the most trade agreements in the world.

Geopolitical Risk and Exchange Rate Return

In the last subsection of analysis, we shall use the monthly GPR index dataset to match with the monthly exchange rate return discussed above. The original dataset consists of 43 country GPR, for the purpose of discussing the GPR in relationship with exchange rate return and due to data availability, we only select 34 countries that prefer using their national currencies.

The GPR indices are measured by Caldara and Iacoviello (2022) based on newspaper articles covering geopolitical tensions, and examine its economic effects since 1900, divided 8 categories: war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, and terror acts. Country-specific GPR index data is a subset of the dataset.

First, we conduct the simple linear regression of the GPR index of each country on its corresponding exchange rate return:

$$EXR_t = \beta_0 + \beta_1 GPR_t + \epsilon_t$$

The regression results are shown in table 4. Clearly, the influence of GPR index on exchange rate returns is vague. The R^2 of all the simple regression models are insignificantly small. The highest R^2 observed is CNY, at 9%, with p-values equal zero. Some other GPR indices that have influence on exchange rate returns at 1% significance level are MXN, NOK and RUB, at 10% significance level is HUF. The slope

Table 4. Regression of Geopolitical Risk on Exchange Rate Return

Index	β_1	β_0	t_0	t_1	p_0	p_1	R^2
ARS	-0.0168	-0.0763	-3.901	-0.655	0.0001	0.513	0.002
AUD	0.0022	-0.0305	0.485	-0.818	0.6281	0.4145	0.0034
BRL	-0.0078	0.0656	-1.362	0.716	0.1748	0.4751	0.0026
CAD	-0.0015	0.0054	-0.39	0.313	0.6966	0.7548	0.0005
CHF	0.001	-0.0039	0.339	-0.087	0.7349	0.9307	0.0
CLP	-0.0021	-0.0155	-0.572	-0.077	0.5678	0.9384	0.0
CNY	0.0063	-0.0099	4.512	-4.605	0.0	0.0	0.0913
COP	-0.0019	-0.0453	-0.501	-0.554	0.6171	0.5803	0.0015
DKK	0.0021	-0.097	0.745	-1.575	0.4572	0.1168	0.0116
EGP	-0.0106	0.0225	-1.696	0.816	0.0913	0.4153	0.0031
GBP	0.0027	-0.005	0.585	-1.176	0.5593	0.2408	0.0065
HKD	-0.0001	0.0009	-0.595	0.61	0.5527	0.5425	0.0018
HUF	-0.0011	-0.0802	-0.372	-1.799	0.7104	0.0734	0.0151
IDR	-0.0074	0.1304	-1.909	1.636	0.0576	0.1033	0.0125
ILS	0.0021	-0.0032	0.746	-0.474	0.4567	0.636	0.0011
INR	-0.0013	-0.0082	-0.377	-0.509	0.7067	0.6113	0.0012
JPY	0.0023	-0.018	0.719	-1.479	0.4729	0.1407	0.0103
KRW	-0.0004	-0.0036	-0.124	-0.403	0.9017	0.6871	0.0008
MXN	-0.0133	0.1178	-2.625	2.376	0.0093	0.0184	0.0261
MYR	-0.0008	-0.0049	-0.511	-0.236	0.6101	0.814	0.0003
NOK	0.0038	-0.1245	1.129	-2.548	0.2602	0.0115	0.0299
PEN	-0.0018	0.0588	-0.945	0.714	0.3456	0.4759	0.0024
PHP	0.0001	-0.0091	0.061	-0.233	0.9516	0.816	0.0003
PLN	-0.0004	-0.0157	-0.141	-1.158	0.8878	0.2482	0.0063
RUB	-0.0118	0.0098	-2.514	2.508	0.0127	0.0129	0.0289
SAR	-0.0001	0.0004	-0.528	0.601	0.5979	0.5483	0.0017
SEK	0.0004	-0.0485	0.143	-1.285	0.8862	0.2001	0.0078
THB	-0.0	0.003	-0.016	0.064	0.9875	0.9487	0.0
TND	-0.0043	0.0085	-2.2	0.323	0.0289	0.7472	0.0005
TRY	-0.0139	0.0058	-2.28	0.308	0.0236	0.7588	0.0004
TWD	0.0027	-0.0464	0.145	-0.257	0.8846	0.7978	0.0003
UAH	-0.0081	-0.0034	-1.561	-0.635	0.12	0.526	0.0019
VEF	-0.0419	-0.4029	-0.683	-0.584	0.4955	0.5597	0.0019
ZAR	0.0009	-0.1291	0.144	-1.115	0.8858	0.2659	0.0059

regression coefficients appear negative most of the time, implying that geopolitical risks tend to have negative effects on the exchange rate returns, in other words, high geopolitical risks are likely to depreciate the national currency, which should be expected by priori reasoning. However, the empirical study of the impacts of GPR on exchange rate returns must deal with a large unexplained variance, which is caused by other factors that are not included in the models. To improve the performance, it is necessary to introduce more independence variables. By looking at the graphical depiction of exchange rate returns over time, we could see that the volatility is not easily captured by a simple linear model. Indeed, to raise the coefficient of determination, we propose adding common predictors, such as oil returns (OIL), stock market returns (MKT), and interest rate (IR):

$$EXR_t = \beta_0 + \beta_1 GPR_{t-1} + \beta_2 OIL_{t-1} + \beta_3 MKT_{t-1} + \beta_4 IR_{t-1} + \epsilon_t$$

So that the model should take the form of a multiple linear regression. Due to the lack of data availability, this project could not experiment on the above model. Instead, we test the two-factor model:

$$EXR_t = \beta_0 + \beta_1 GPR_{t-1} + \beta_2 IR_{t-1} + \epsilon_t$$

The country-specific monthly interest rate data are downloaded from OECD website, in the period from January 2005 to October 2022, consisting of 43 countries. We filtered to pull out only 19 countries that match our project. The regression results are reported in table 5.

As can be seen, R^2 increased when we add more variables to the model, though not significantly. For example, the regression on JPY and KRW had R^2 increased from 0.01 to 0.035, and 0.0008 to 0.0132, respectively, because of the newly added variable. The p-value of β_1 in the regression of IDR has decreased to 0.07, at which we can reject the null hypothesis. Afterall, this is still a "bad" model, as it does not capture much of the explained variables.

Table 5. Regression of Geopolitical Risk and Interest Rates on Exchange Rate Return

Index	β_1	β_2	β_0	t_1	t_2	p_1	p_2	R^2
AUD	0.006	-0.0415	-0.0009	-1.005	-0.624	0.3161	0.5335	0.0054
CAD	-0.0007	0.0061	-0.0005	0.349	-0.369	0.7277	0.7124	0.0011
CHF	0.0006	0.0009	0.0012	0.021	0.577	0.9836	0.5645	0.0016
CLP	0.0025	-0.0235	-0.001	-0.109	-0.632	0.9134	0.5283	0.0026
CNY	0.0062	-0.0099	0.0	-4.563	0.072	0.0	0.9426	0.0913
COP	-0.0019	-0.0457	-0.0	-0.548	-0.013	0.5841	0.9895	0.0015
DKK	0.0018	-0.0953	0.0002	-1.527	0.165	0.1283	0.8693	0.0117
GBP	0.004	-0.0046	-0.001	-1.088	-1.155	0.2779	0.2494	0.0129
HUF	0.0001	-0.0807	-0.0005	-1.807	-0.554	0.0724	0.5802	0.0179
IDR	-0.011	0.1671	0.0004	1.791	0.283	0.0747	0.7777	0.0183
INR	0.0017	-0.0161	-0.0004	-0.679	-0.327	0.4981	0.7441	0.0037
ILS	0.0018	-0.004	0.0004	-0.561	0.379	0.5752	0.7049	0.0018
JPY	-0.0032	-0.0103	0.0156	-0.821	2.276	0.4126	0.0238	0.0342
KRW	0.0078	-0.0066	-0.0028	-0.731	-1.623	0.4655	0.106	0.0132
MXN	-0.0105	0.1238	-0.0005	2.38	-0.418	0.0182	0.6767	0.0267
NOK	0.0083	-0.1365	-0.0019	-2.739	-1.159	0.0067	0.2479	0.0364
RUB	-0.0085	0.0076	-0.0001	1.867	-0.136	0.0634	0.8921	0.0172
SEK	0.002	-0.0575	-0.0016	-1.471	-0.932	0.1428	0.3526	0.0118
ZAR	0.0025	-0.1259	-0.0003	-1.083	-0.149	0.28	0.8813	0.0057

We could try adding more variables if data are available, however, the large error term is a big challenge. This could be caused by the non-normal distribution of the original data. To avoid this, we probably could normalize the data beforehand. Finally, if we need not use the real exchange rate returns as a regressand, we could use some other variables to "adjust" the regressand, making it "smoother". We could use adjusted exchange rate returns, as a proxy to the real exchange rate returns. To do so, Iyke et al., 2022 have successfully estimated adjusted exchange rate returns by the linear regression, eliminated the effects of oil returns, stock market returns and interest rates, then established a simple linear regression of GPR index on exchange rate returns. The result shows that geopolitical risk is economically significant in exchange rate models, where it could predict the returns in more than half of the countries. However, they did not report the percentage of exchange rate returns explained by the GPR index, which should also be considered when performing regressions.

Conclusions

This project has been carried out on three datasets, with the exchange rate return is our primary concerns in analysis. Besides, we questioned whether the geopolitical risk have effects on the exchange rate return, and lastly, we added the monthly country-specific interest rate data to test the effects of geopolitical risk.

The result shows that exchange rate returns are not close to normal distribution. In fact, they tend to be negatively skewed and heavy-tailed. It also shows that the distribution of exchange rate returns differs from country to country, probably owing to difference in many macro-factors. This proposes further study on which macro-factors would affects the exchange rate returns' distributions.

In the single exchange rate analysis, we have calculated the confidence interval for each return's mean and variance, to improve our understanding of the distribution. We also performed the first-order autoregression models to test whether the exchange rate returns are correlated over time. The historical returns are statistically significance for some exchange rates, for example, CNY and TWD. However, we suppose that the exchange rate return with high volatility could not be explained by one single period autoregressive model, but probably requires much more complex non-linear algorithms.

In the two-exchange rate analysis, we first used t-test to test the difference in the mean of the paired sample. The result shows that the null hypothesis could be rejected most of the time. We also used simple linear regression to estimate the relationship between the log-return of one exchange rate on others, and the results are difference for each country. One possible hypothesis for further testing is that the exchange rate returns of the countries in European tend to be more correlated to each other, whereas the exchange rates of some Asian countries behaved more independently.

In the last subsection of the project, we explored the impacts of geopolitical risks on exchange rate returns. Despite the large variance of the exchange rate data, we still tried to implement linear regression method. The unconditional linear regression's result shows that most geopolitical risks have negative effects on exchange rate returns. To improve the performance, first we propose adding more regressors to the models, for example, oil returns, stock market returns and interest rates. Due to the lack of resources, we only added monthly interest rates to the model. The R^2 improved, though insignificantly. In further study, we should somehow normalize the data, collect more observations, or adjust our dependent variables to reduce the error terms, for example, eliminate the impacts of oil returns, stock market returns and interest rates from the model.

The experiments were carried out on Google Collaboratory, written in Python language. The codes, which should provide a more thorough information about the methods, can be found here.

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