

The International Effects on the Job Market: Exploring Exchange Rates and Unemployment

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I. Abstract

This paper takes a stab at understanding the statistical relationship between various exchange rates of a country and the unemployment rate in that same country. In order to study this question, we looked at the U.S.' currency in relation to other large trading partners such as Canada, Mexico, China, etc and the unemployment rate in the U.S. We initially believed that higher exchange rates would yield lower unemployment rates because the economy is generally expanding. We eventually found this to be true at a statistically significant level.

II. Introduction and Purpose

The relationship between exchange rates and unemployment can be complex and multifaceted. Changes in exchange rates can have a significant impact on a country's economy, particularly its exports and imports, and therefore, can affect the level of unemployment. For example, when a country's currency appreciates, its exports become more expensive, making them less competitive on the international market, and this can lead to a decline in demand for the country's products, ultimately affecting employment in the export sector.

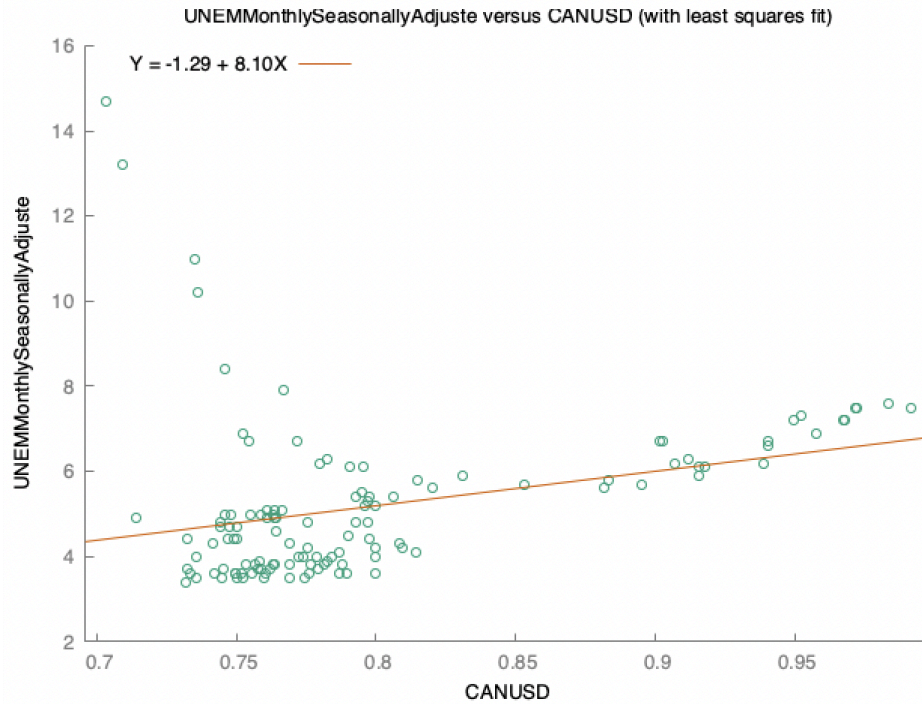
Similarly, changes in exchange rates can also have an impact on the cost of imports, which can affect employment in the domestic industries that rely on imported goods. For instance, if a country's currency depreciates, the cost of importing raw materials and goods becomes more expensive, and this can lead to higher production costs, lower profits, and potentially job losses.

Overall, the relationship between exchange rates and unemployment is complex and can be influenced by a wide range of factors. Understanding this relationship is essential for policymakers and economists, as it can help them to develop effective strategies for managing and stabilizing the economy in times of volatility. Therefore we look to explore the relationship between various exchange rates and unemployment rates statistically to help governments navigate and read international signals that may affect the economy.

III. Data

Our Data is pulled directly from the FRED. Specifically, we pulled Exchange Rate Data from a motley of countries that trade with the US along with Sticky CPI and United State Unemployment Data. Our data is time-series and monthly.

The key relationship we seek to investigate in this paper is between the Exchange Rates of various currencies to the US's unemployment rate. We denote our key independent variable (CAN Dollar to USD Exchange Rate) by ***CanUSD (1)***, and our key dependent variable (UnemploymentRate) as ***UNEM (11)***. A scatterplot of the data representing this relationship as well as a simple regression line is shown below. Based on this plot, we observe a weak, positive relationship between the Canadian Dollar to USD Exchange Rate and the Unemployment Rate.



We also show descriptions and statistics for all of our variables in the table below:

Variable(#)	Description	Unit	Source
CANUSD (1)	The Exchange Rate of Canadian Dollars per United States Dollar. (Monthly)	Canadian Dollar/USD	https://fred.stlouisfed.org/series/DEXCAUS
EuroUSD (2)	The Exchange Rate of Euros per United States Dollar. (Monthly)	Euro/USD	https://fred.stlouisfed.org/series/DEXUSEU
ChineseYMB USD (3)	The Exchange Rate of the Chinese RenMinbi per United States Dollar. (Monthly)	ChineseRenMinbi/USD	https://fred.stlouisfed.org/series/DEXCHUS
SKWUSD (4)	The Exchange Rate of South Korean Won per United States Dollar. (Monthly)	SKWon/USD	https://fred.stlouisfed.org/series/DEXKOUS
PesosUSD (5)	The Exchange Rate of Pesos per United States Dollar. (Monthly)	Pesos/USD	https://fred.stlouisfed.org/series/DEXMXUS




RupeeUSD (6)	The Exchange Rate of Rupees per United States Dollar. (Monthly)	Rupee/USD	https://fred.stlouisfed.org/series/DEXINUS
StickyCPIInflation (7)	The percentage of total league cap space allocated to all of the linebackers on a given team's roster. (Monthly)	Inflationary Units%	https://fred.stlouisfed.org/series/CORESTICKM159SFRBATL
UNEM(8)	The seasonally adjusted Unemployment Rate. (Monthly)	Unemployment%	https://fred.stlouisfed.org/series/UNRATE

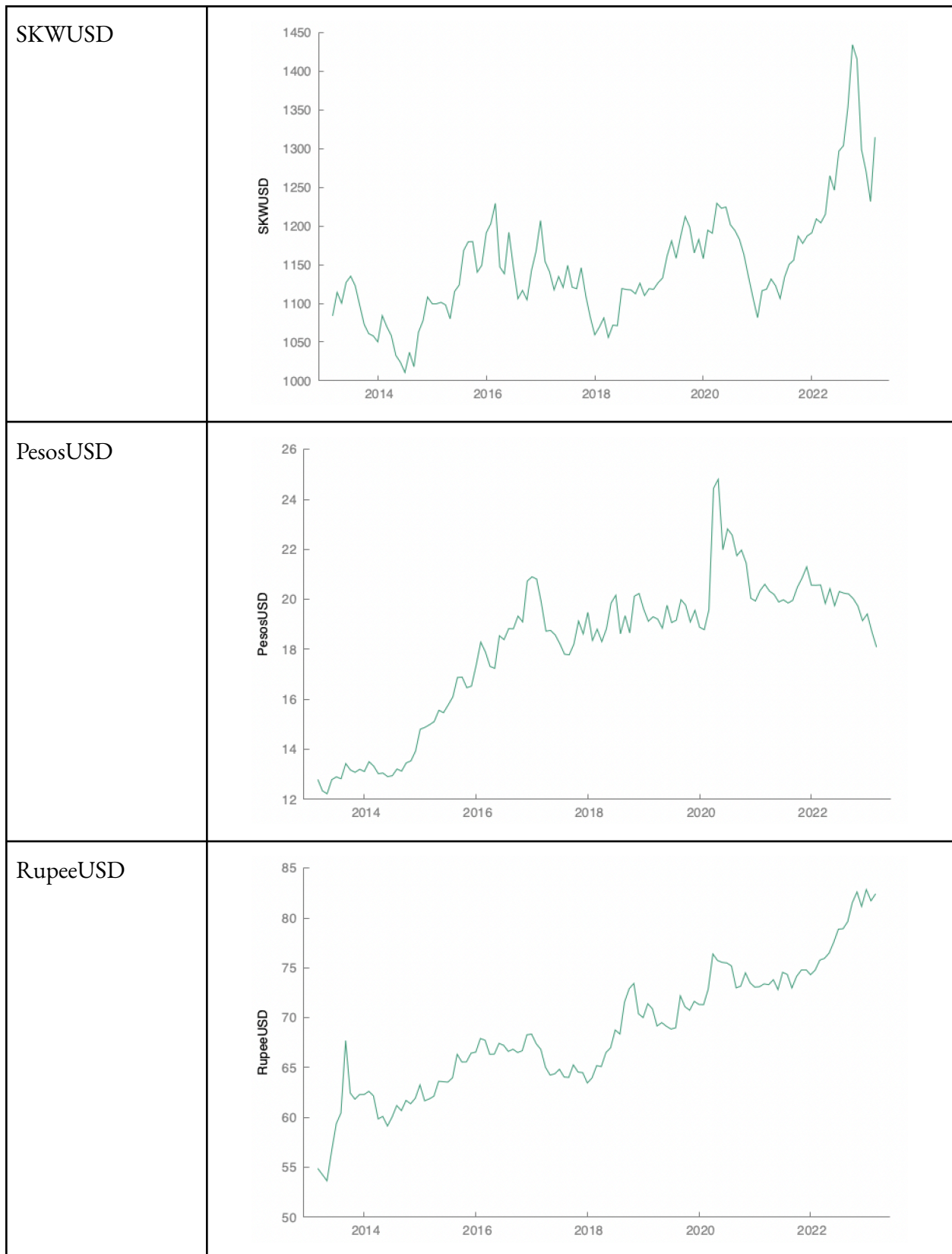
Table 1: Data Description

Variable Name	Number of Observations	Mean	Standard Deviation	Minimum	Maximum	Skewness
CANUSD	121	0.7986	0.0702	0.7031	0.9918	-1.3764
EuroUSD	121	0.8646	0.0665	0.7211	1.0195	-0.4179
ChineseYMBUSD	121	6.568	0.3168	6.050	7.273	0.1515
SKWUSD	121	1147	73.89	1011	1435	1.1850
PesosUSD	121	18.11	2.896	12.22	24.81	0.5717
RupeeUSD	121	68.61	6.349	53.65	82.86	0.1459
StickyCPIInflation	121	2.703	1.209	1.517	6.617	2.242
UNEM	121	5.183	1.838	3.400	14.70	2.2332

Table 2: Descriptive Statistics

Variable Name	Time Series Plots
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CANUSD	
EuroUSD	
ChineseYMBUSD	



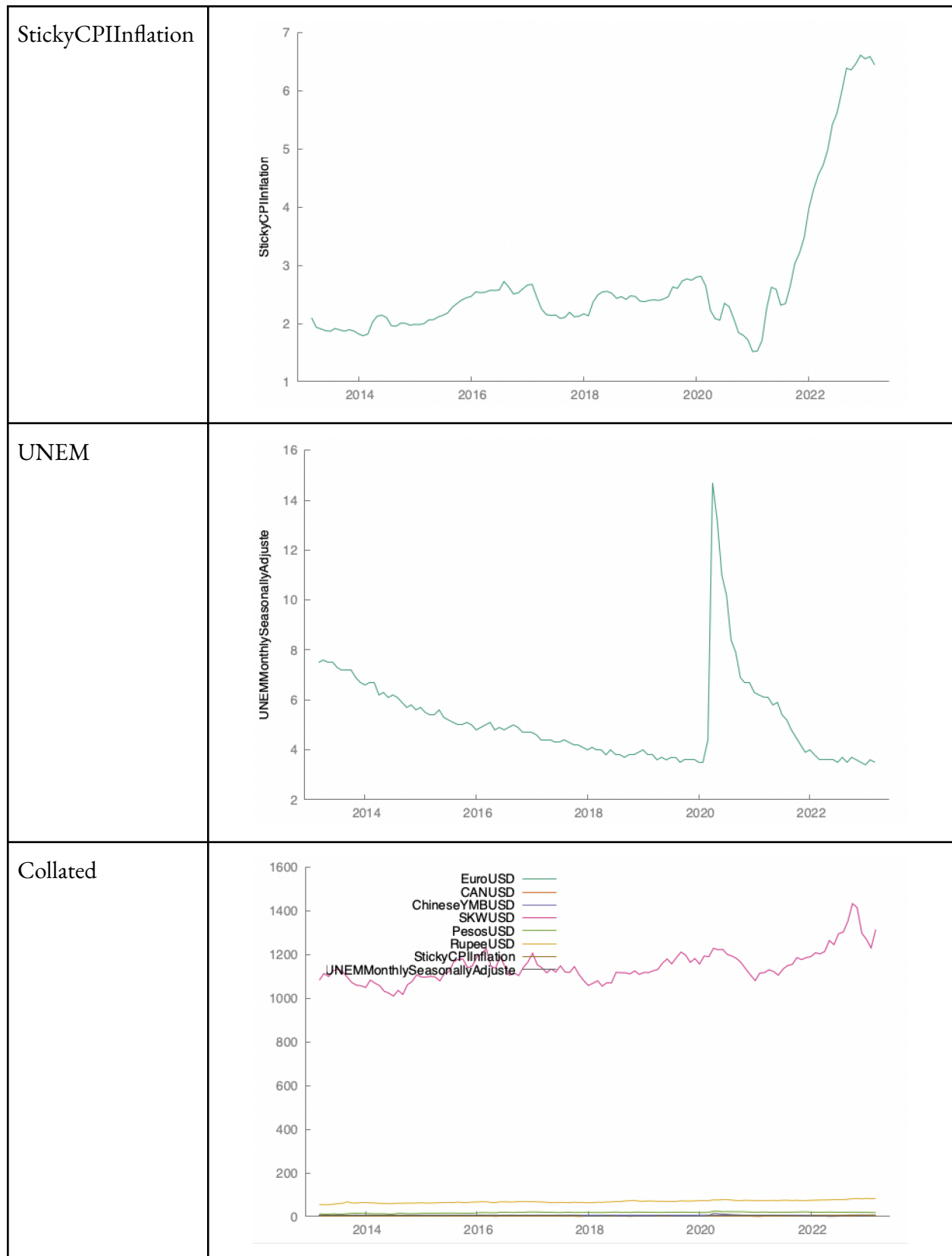


Table 3: Time Series Plots

V. Regressions

A. Simple Regression

In our simple regression, we regress the United States' seasonally adjusted monthly unemployment rate (UNEM) on the exchange rate between the Canadian and US dollar (CANUSD). The resulting equation is as follows:

$$UNEM = \beta_0 + \beta_1 CANUSD.$$

Within our regression, we expect a negative coefficient ($\beta_1 < 0$) on CANUSD. As the American dollar appreciates relative to its Canadian counterpart, the cost of Canadian imports falls, which causes American demand for them to rise. This, in turn, might cause domestic companies to reduce their costs by eliminating jobs—raising unemployment in the process. However, we expect significant omitted variable bias (OV) tied to this model. Canadian imports, for instance, only comprise a small portion of American goods; since this fraction is higher for other large exporters, we expect a strong bias. Moreover, we expect the direction of this bias to be negative—international exchange rates should be relatively uncorrelated, but in general should demonstrate a negative correlation with American unemployment.

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Model 4: OLS, using observations 2013:03–2023:03 (T = 121)
Dependent variable: UNEMMonthlySeasonallyAdjuste
HAC standard errors, bandwidth 3 (Bartlett kernel)
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	coefficient	std. error	t-ratio	p-value
const	-1.28557	3.48817	-0.3686	0.7131
CANUSD	8.10039	4.07921	1.986	0.0494 **

Mean dependent var	5.183471	S.D. dependent var	1.838312
Sum squared resid	366.7719	S.E. of regression	1.755596
R-squared	0.095567	Adjusted R-squared	0.087967
F(1, 119)	3.943299	P-value(F)	0.049358
Log-likelihood	-238.7830	Akaike criterion	481.5660
Schwarz criterion	487.1576	Hannan-Quinn	483.8370
rho	0.819005	Durbin-Watson	0.362126

Our model demonstrates that a 1 point increase in Canadian-American exchange rate corresponds to a 8.1% increase in US unemployment. With a p-value of 0.0494, this coefficient is significant to the 5% level. However, the R^2 value of 0.095 and the adjusted R^2 value of 0.087 demonstrate that very little of the variation in unemployment can be explained by CANUSD.

B. Multiple Regressions

To address the potential bias, we run a multiple regression that includes 6 other covariates: the exchange rates between the US and major exporters like China, Korea, Mexico, India, and the EU, as well as domestic rates of inflation.

$$Unem = \beta_0 + \beta_1 CANUSD + \beta_2 EuroUSD + \beta_3 ChineseYMBUSD + \beta_4 SKWUSD + \beta_5 PesosUSD + \beta_6 RupeeUSD + \beta_7 StickyCPIInflation + \beta_8 Time$$

Adding these explanatory factors to our specification, we observe a few distinct changes. First, the coefficient on CANUSD increases in both magnitude and statistical significance (a point we will return to further on). However, most exchange rates are insignificant at the 5% level—including PesosUSD, RupeeUSD, EuroUSD, and YMBUSD (Chinese Yuan). Interestingly, while the first three nations are not large American trade partners, the United States imports nearly a third of its goods from China and Canada. It is surprising, therefore, that only one of these nations' currencies demonstrates statistical significance in our model.

Model 1: OLS, using observations 2013:03–2023:03 (T = 121)				
Dependent variable: UNEMMonthlySeasonallyAdjuste				
HAC standard errors, bandwidth 3 (Bartlett kernel)				
	coefficient	std. error	t-ratio	p-value
const	-21.8247	11.6027	-1.881	0.0625 *
StickyCPIInflati~	-1.35833	0.396055	-3.430	0.0008 ***
EuroUSD	-8.07468	6.99527	-1.154	0.2508
CANUSD	13.4218	4.62512	2.902	0.0045 ***
ChineseYMBUSD	-0.340603	1.02093	-0.3336	0.7393
SKWUSD	0.0197594	0.00762429	2.592	0.0108 **
PesosUSD	0.183928	0.204422	0.8997	0.3702
RupeeUSD	0.0463514	0.0562717	0.8237	0.4118
Mean dependent var	5.183471	S.D. dependent var	1.838312	
Sum squared resid	220.4060	S.E. of regression	1.396602	
R-squared	0.456495	Adjusted R-squared	0.422826	
F(7, 113)	14.60399	P-value(F)	1.97e-13	
Log-likelihood	-207.9723	Akaike criterion	431.9445	
Schwarz criterion	454.3108	Hannan-Quinn	441.0283	
rho	0.716720	Durbin-Watson	0.562489	
Excluding the constant, p-value was highest for variable 6 (ChineseYMBUSD)				

C. Time Trend

One potential shortcoming of this model is its inability to capture changes in the American unemployment rate that occur simply due to the passage of time. To account for this, we include a linear time trend (time) in our regression.

Model 2: OLS, using observations 2013:03–2023:03 (T = 121)
 Dependent variable: UNEMMonthlySeasonallyAdjuste
 HAC standard errors, bandwidth 3 (Bartlett kernel)

	coefficient	std. error	t-ratio	p-value	
const	-30.0497	14.0379	-2.141	0.0345	**
EuroUSD	-13.1346	8.58872	-1.529	0.1290	
CANUSD	14.0161	6.01225	2.331	0.0215	**
ChineseYMBUSD	-0.629065	0.824349	-0.7631	0.4470	
SKWUSD	0.0170471	0.00636443	2.678	0.0085	***
PesosUSD	0.569889	0.299046	1.906	0.0593	*
RupeeUSD	0.229119	0.0988687	2.317	0.0223	**
StickyCPIInflati~	-0.856373	0.293436	-2.918	0.0043	***
time	-0.0615123	0.0261465	-2.353	0.0204	**
Mean dependent var	5.183471	S.D. dependent var	1.838312		
Sum squared resid	176.0584	S.E. of regression	1.253774		
R-squared	0.565853	Adjusted R-squared	0.534842		
F(8, 112)	8.194532	P-value(F)	1.11e-08		
Log-likelihood	-194.3806	Akaike criterion	406.7612		
Schwarz criterion	431.9233	Hannan-Quinn	416.9805		
rho	0.691741	Durbin-Watson	0.607625		

Excluding the constant, p-value was highest for variable 4 (ChineseYMBUSD)

Detrending the data has a number of implications. First, we observe the emergence of statistical significance on the coefficients SKWUSD, PesosUSD, RupeeUSD, and time. This suggests that in our original regression, the statistical effect of the omitted time trend did, in fact, confound the significance of our other explanatory measures; detrending solves this problem. However, a majority of the coefficients still do not align with our initial expectations. Five of the six exchange rates now demonstrate significant, positive relationships; the one negative (though insignificant) association we find is between the Yuan-USD exchange rate and unemployment.

D. Multicollinearity

To further investigate the relationships derived from our model, we test our explanatory factors for collinearity.

Variance Inflation Factors	
Minimum possible value = 1.0	
Values > 10.0 may indicate a collinearity problem	
StickyCPIInflation	5.827
EuroUSD	10.044
CANUSD	9.742
ChineseYMBUSD	3.051
SKWUSD	6.476
PesosUSD	10.448
RupeeUSD	12.002
time	12.595

The corresponding variable inflation factors (VIFs) indicate that EuroUSD, CANUSD, PesosUSD, and RupeeUSD demonstrate collinearity. In our next regression, we test a reduced-form model that omits these variables:

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Test on Model 2:

Null hypothesis: the regression parameters are zero for the variables
EuroUSD, ChineseYMBUSD
Test statistic: Robust F(2, 112) = 1.71553, p-value 0.184561
Omitting variables improved 1 of 3 information criteria.

Model 4: OLS, using observations 2013:03-2023:03 (T = 121)
Dependent variable: UNEMMonthlySeasonallyAdjuste
HAC standard errors, bandwidth 3 (Bartlett kernel)


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	coefficient	std. error	t-ratio	p-value	
const	-48.0902	16.6407	-2.890	0.0046	***
CANUSD	24.0576	6.43094	3.741	0.0003	***
SKWUSD	0.0110947	0.00488106	2.273	0.0249	**
PesosUSD	0.514076	0.313562	1.639	0.1039	
RupeeUSD	0.267225	0.110356	2.421	0.0170	**
StickyCPIInflati~	-1.07230	0.299215	-3.584	0.0005	***
time	-0.0558993	0.0269170	-2.077	0.0401	**
Mean dependent var	5.183471	S.D. dependent var	1.838312		
Sum squared resid	186.3088	S.E. of regression	1.278393		
R-squared	0.540576	Adjusted R-squared	0.516396		
F(6, 114)	8.196842	P-value(F)	2.23e-07		
Log-likelihood	-197.8043	Akaike criterion	409.6085		
Schwarz criterion	429.1791	Hannan-Quinn	417.5569		
rho	0.709107	Durbin-Watson	0.579796		

Excluding the constant, p-value was highest for variable 6 (PesosUSD)

Since the p-value corresponding to the F-test is greater than 0.05, the omitted variables do not demonstrate joint significance. This aligns with the expectation that international exchange rates should not be tied to one another, and suggests that the individually insignificant coefficients from the previous regression simply lack the requisite explanatory power in our model.

VI. Conclusion

In conclusion, as we hypothesized, we found that exchange rates are a clear indicator of how an economy's unemployment rate is varying. While some rates have a larger effect than others due to the strength of their ties with the U.S., most rates were significantly effective in determining the unemployment rate. We also find that combinations of rates have no effect or joint significance on the unemployment rate which makes intuitive sense since groups of countries are not trading with the U.S. Ultimately, we observe a strong relationship between nations' exchange rates and their unemployment rates, however we use only strong trading partners with the U.S. In the future, we hope to determine whether any random exchange rate has a natural, significant correlation with the unemployment rate.

IX. References