Changing Currency Preference in Major Economies

1. Motivation

The Cambridge Dictionary defines currency as money used in a particular country at a specific time. It also defines money as coins or notes used to buy things. Although the issuing government typically authorises and regulates its currency, the value of that currency is dynamic and influenced by various macroeconomic factors. For instance, In a high-inflation environment, purchasing power decreases, whereas in a high-deflation environment, it increases.

However, it is far more common to see high levels of inflation than high levels of deflation. Consumers typically handle inflation by increasing their income or decreasing their spending. They can also exchange their money for a different, less volatile currency that holds or increases its value.

A cryptocurrency is a "digital asset that uses distributed ledger, or blockchain technology to enable a secure transaction" (Härdle, Harvey, & Reule, 2020). However, the primary use of cryptocurrencies is no longer purchasing goods and services. The Securities and Exchange Commission (SEC) classifies cryptocurrencies and other similar digital assets as securities—specifically "investment contracts"—because there is a reasonable expectation of profits from acquiring cryptocurrencies.

Since the creation of Bitcoin in 2009 by the anonymous group or individual known as Satoshi Nakamoto, the number of cryptocurrencies and cryptocurrency users has increased dramatically. "More than 1,600 cryptocurrencies have entered into circulation" (Rejeb, 2020), and "the global user base of cryptocurrencies [has] increased by nearly 190 percent between 2018 and 2020" (de Best, 2024). Meanwhile, in 2022, both the UK and the US experienced their highest levels of inflation of the 21st century (US Bureau of Labor Statistics; Office for National Statistics). Therefore, in this study, I will explore whether changes in the value of traditional currencies have had a statistically significant relationship with the growing usage of cryptocurrencies.

2. Key Variables

Market Cap (Crypto): To model the relationship between the changing value of fiat currencies and the increasing usage of cryptocurrency over time, I will use a regression with panel data. I use the total market capitalisation of the cryptocurrency market globally as a proxy for cryptocurrency usage.

$$Market\ Cap = Price\ per\ Unit\ \times\ Circulating\ Supply$$

Inflation Rate (inf): I use the inflation rate (calculated using the Consumer Price Index) as the primary measure of the rate and magnitude of changes in a currency's value. High inflation rates can potentially increase the use of alternative currencies and assets.

Interest Rate (int): Interest rates have several effects on the economy because they indicate the cost of borrowing money. A higher interest rate usually implies lower borrowing, higher savings, and slower overall economic activity. Central banks use interest rates to help regulate the economy. Therefore, by including interest rates in the model, I aim to capture the effect of monetary policy on shifting investors toward alternative investments (i.e., cryptocurrencies) and account for other short-term effects not yet reflected in the inflation rate.

Gross Domestic Product (GDP): I also include Gross Domestic Product (GDP) to account for other economic conditions that might influence cryptocurrency usage. GDP is calculated as the total value of all final goods and services produced or consumed across the entire economy. Because the GDP is often used as an indicator of the overall health and growth of the economy, it is included as a "catchall" variable to reduce the risk of bias from omitted variables.

Macroeconomic Shock (Shock): Major international or even global events - such as the 2008 financial crisis or the 2020 pandemic - are irregular but cause substantial disruptions. Therefore, to account for these disruptions, I include a dummy variable. This variable has a value of 1 during a year affected by a major shock and zero otherwise. Including this variable helps isolate exogenous shocks that contribute to higher fiat currency volatility and cryptocurrency adoption.

Exchange Rate (CNY, INR, USD, EUR): Currencies change in value through the purchasing power of their assets. However, they can also change relative to other currencies with their ability to purchase foreign assets. Exchange rates are another commonly used metric for currency appreciation and depreciation. Therefore, I use the exchange rates between currencies to capture the relative purchasing power of each currency.

Internet Penetration Rate (IPR): Finally, the Internet penetration rate (IPR) is "the number of Internet users per 100 inhabitants" (Pratama, 2012). The most basic requirement for accessing any cryptocurrency is a computer or digital device, as all cryptocurrencies are digital assets. Consequently, cryptocurrency usage is highly correlated with the number of people who have Internet access. I use the IRP as a proxy for this value, hoping to further reduce the risk of omitted variables.

3. Data

Several metrics can be used to measure cryptocurrency usage over time, such as average daily transaction volume or number of unique crypto wallet addresses. Additionally, because the panel data model looks at several countries across time, the best practice would be to use a dependent variable for each country and each period. However, the most important factor to consider is the availability, consistency, and reliability of the data. The estimations of all the aforementioned metrics vary drastically depending on the source and are generally only available for 2017 to the present day. Therefore, I will use the cryptocurrency market cap as the data for the cryptocurrency market cap is available and consistent from as early as 2013.

There are approximately 562 million cryptocurrency users worldwide (Triple-A, 2024). Of those 562 million, nearly 75 million are in North America, 50 million in Europe, and over 300 million in Asia, creating a clear majority. Therefore, the model will use data from China, India, the European Union (EU), and the United States (US).

Furthermore, these four regions account for a large share of the global GDP. Because of the large size of their economies, there is more reliable and readily available data on cryptocurrency usage as well as economic data and government statistics.

Consequently, I will use the inflation rates of the Chinese Yuan, Indian Rupee, US Dollar and Euro. All the inflation data was sourced from the respective national statistics agencies (i.e., The National Bureau of Statistics of China, The Ministry of Statistics and Programme Implementation (MoSPI) in India, the US Bureau of Labour Statistics, and Eurostat).

The names of the interest rates used for each country varied slightly but generally represented the same concept. Most of the central banks of all the countries set several rates. Therefore, These are the rates I will use:

Functionally, the Main Refinancing Operations Rate (set by the The European Central Bank) most closely resembles conventional interest rates, as it directly influences banks' borrowing and lending costs and affects liquidity in the economy. Therefore, I will use the Main Refinancing Operations Rate for the EU.

The Medium-Term Lending Facility one-year interest (set by The People's Bank of China) will be used because it is the rate at which the central banks influence short-term borrowing for the commercial banks.

The Federal Reserve uses the federal fund's effective rate as its benchmark interest rate, and I will use the repo rate as the interest rate for India, as it represents the short-term lending rate provided by the RBI to banks.

To find the overall monetary environment and the long-term effects, I will use the average interest rates across the entire year for each country.

The exchange rates between two currencies can either be very stable or very volatile. Additionally, the range of values an exchange rate can take is very large, such as the USD to EUR conversion fluctuating around 1.00 EUR per USD, but the USD to INR conversion starting around 45 INR per USD in the early 2000s and being higher than 80 INR per USD since 2022. As such, I look at the percentage change of the exchange rate to maintain stationarity and a consistent scale for the model.

While interest and inflation rates typically fluctuate within a relatively small range, GDP, and the global cryptocurrency market cap compound over time, reaching much larger magnitudes. Therefore, for comparability, I used the annual percentage change. This approach supports more consistent comparisons of these variables across time and helps ensure that GDP and market cap remain stationary, thus reducing potential bias and inconsistency in the models. It also means that the model is not biased by the larger or smaller economies, and simply observes how the rate of growth of the economy affects the rate of growth of the cryptocurrency market.

The GDP data came from the relevant government agencies (i.e., the US Bureau of Economic Analysis (BEA), the National Bureau of Statistics (NBS) of China, the Central Statistics Office (CSO) in India, and Eurostat).

Internet penetration is generally a good indicator of how connected a country is. However, countries like India and China have a relatively small IPR with hundreds of millions of internet users due to their large populations. On the opposite extreme, the US and the EU have much higher IPRs and therefore exhibit less change or growth.

Therefore, to balance this out, I will use the percentage change of the IPR with a weight. The weight is calculated using the average percentage change in the IPR relative to the other regions' average IPR percentage change:

$$\Delta IPR_{i,t} = \frac{IPR_{i,t} - IPR_{i,t-1}}{IPR_{i,t-1}} * 100$$

$$\overline{\Delta IPR_i} = \frac{\sum_{t=1}^{T} \Delta IPR_{i,t}}{T}$$

$$w_i = \frac{\overline{\Delta IPR_i}}{\sum_{i=1}^{4} \overline{\Delta IPR_i}}$$

The average percentage changes in IPR for China, India, the US and the EU are 6.32%, 15.97%, 2.63% and 2.06%. Therefore, the resulting weights are 0.234, 0.592, 0.098, and 0.076 respectively.

All data used in the model spans the years 2014 to 2023 in annual intervals around the end of each year.

While several years can be considered for major macroeconomic shocks, in the model, I will only use 2018, 2019, 2020 and 2022. In 2018 and 2019, the China-US trade war began and resulted in large tariffs on over 350 billion USD of Chinese imports into the US and 100 billion USD of American exports to China (Fajgelbaum, Khandelwal 2021). In January 2020, The United Kingdom officially left the EU, and the World Health Organisation declared the COVID-19 outbreak a (PHEIC) public health emergency of international concern (World Health Organisation 2020), taking a toll of almost 14 trillion USD in the US alone (Hlavka, Rose 2023). In 2022, Russia advanced its invasion of Ukraine, which amounted to a total cost of 1.5 trillion USD or about 1% of the global GDP (Liadze, Macchiarelli, Mortimer-Lee, Juanino 2023). Therefore, because of the immense scale of these global events and their relevance to the chosen regions, they will be considered as macroeconomic shocks.

4. The model

A Pooled Ordinary Least Squares (POLS) is a panel data model that involves pooling data for all individuals across all periods and treating it as one large cross-sectional dataset. A POLS model serves here as the baseline.

$$\Delta Crypto_{i,t} = \beta_0 + \beta_1 inf_{i,t} + \beta_2 int_{i,t} + \beta_3 \Delta GDP_{i,t} + \beta_4 w_i \Delta IPR_{i,t} + \beta_5 \Delta CNY_{i,t} + \beta_6 \Delta INR_{i,t} + \beta_7 \Delta USD_{i,t} + \beta_8 \Delta EUR_{i,t} + \beta_9 Shock_{i,t} + \alpha_i + \lambda_t + \epsilon_{i,t}$$

$$i \in \{China, India, US, EU\}$$

$$t \in \{2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023\}$$

The term α_i is unobserved country-specific effects, λ_t is time effects common to all countries, and $\epsilon_{i,t}$ is the idiosyncratic error term. POLS models have the advantage of simplicity. However, they also have several shortcomings:

Firstly, the independence and rank condition assumptions state that the observations and independent variables should be independent of each other. In this context, it is unrealistic to assume full independence because the countries interact economically, and historical events influence future decisions. Violating the independence assumption leads to inefficient estimates, and cluster-robust standard errors must be used.

Secondly, POLS models do not account for the unobserved heterogeneity (the component that does not change over time). If the correlation between the independent variables and the unobserved effect is non-zero, the POLS estimates suffer from heterogeneity bias. As a solution, the unobserved effect will be differenced away using a Fixed Effect (FE) and Random Effect (RE) model.

The multicollinearity assumption (the independent variables should not be highly correlated with each other) is essential to consider when creating a multiple linear regression model. However, estimates of the parameters become biased when relevant variables are omitted. As such, even though there might be a strong relationship between the independent variables, they were all included because they are valuable indicators and represent different aspects of the economy.

5. Results

Table 5.1 Summary Statistics

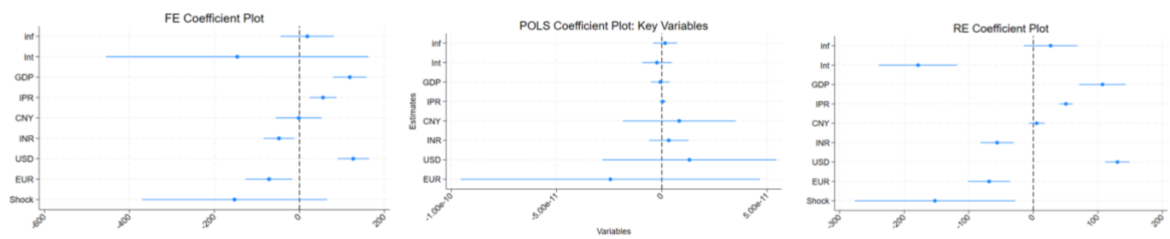
	Inf	Int	GDP	IPR	CNY	INR	USD	EUR	Shock
China	1.75	3.10	5.96	6.32	0.00	1.53	-1.46	0.75	0.40
India	5.14	5.99	6.00	15.97	-1.20	0.00	-2.71	-0.51	0.40
US	2.73	1.28	2.32	2.63	1.74	2.99	0.00	2.49	0.40
EU	2.32	0.46	1.73	2.06	-0.41	0.92	-1.85	0.00	0.40
	2.99	2.71	4.00	6.74	0.03	1.36	-1.50	0.68	

Depreciation
0.20
-1.10
1.80
-0.34

Above is a table summarising the average values of each country between 2014 and 2023. Underneath are the average values for each variable for all the countries across all the time periods. China and India are both developing nations while the US and the EU are both developed regions. This is reflected in the data, with India and China exhibiting higher interest rates, GDP growth rates, and IPR growth rates (before adding weight).

An interesting finding came in the exchange rates. The US appeared to have the most appreciation, as the amount of every other currency it was able to buy increased by an average of 1.8% every year. Additionally, every other currency was able to buy an average of 1.5% less USD every year. On the opposite extreme was India which faced the highest depreciation relative to all the other currencies. It lost the ability to purchase an average of 1.1% of every other currency each year and became an average of 1.36% cheaper to buy each year. Other insights of the variables are further expanded upon in the next sections.

Figure 1: Regression with 2018 Shock Coefficient plots



I ran 3 regressions (POLS, FE and RE). All the regressions used cluster robust standard errors to account for dependent data. I found that across all three, there were not any variables that affected the growth rate of the cryptocurrency market. However, one key thing to not is that even with clustering, the POLS model exhibited extremely high multicollinearity. The year 2022 was excluded due to collinearity, and the R-squared was 100%, likely indicating the multicollinearity. Therefore, I did a Variance Inflation Factor (VIF) test to quantify collinearity and found a mean VIF of 310.16. As such, I only used the findings from the FE and RE models.

Using the RE and FE models, I found that the exchange rate with the USD most consistently had the highest positive statistically significant effect on the cryptocurrency growth rate. After that, the change in GDP and IPR has the next largest, statistically significant effect on the cryptocurrency market growth rate. Both conclusions make sense for several reasons. Firstly, as was previously stated, because cryptocurrencies are a digital asset, a larger online population means that more people have access to cryptocurrencies, and the likelihood of people owning cryptocurrencies increases. Additionally, because China and India have the largest populations in the world, an average increase of 6.32% and 15.97% every year means tens of millions if not hundreds of millions of new users.

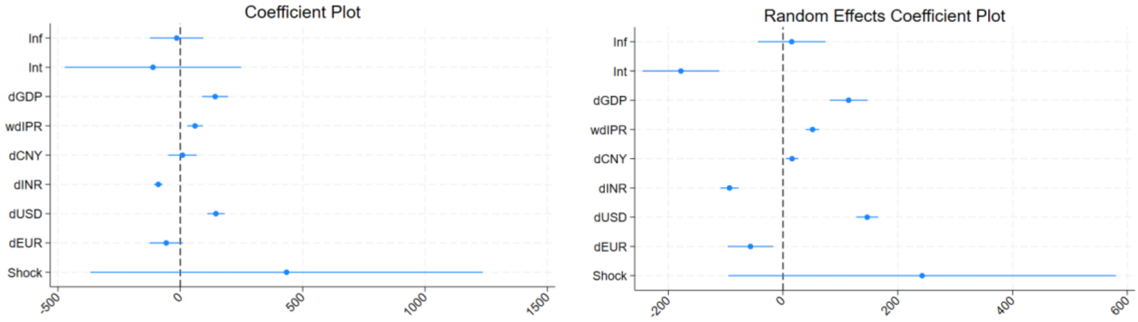
Secondly, more GDP growth can lead to more cryptocurrency because a wealthier population has more disposable income (particularly since average GDP growth was higher than the average inflation) to invest in alternative assets such as cryptocurrencies. Additionally, cryptocurrencies are not regulated by governments in the same way that fiat currencies are regulated, but they are still contained within a larger economy. This could be a case of reverse causality as well. Because cryptocurrencies are quite volatile and often experience exponential, a cryptocurrency market cap in the trillions makes up a substantial share of the global GDP and might account for a higher GDP growth rate.

A strong relationship with the USD exchange rate might not be immediately obvious. However, because the USD is the world's principal reserve currency, and it exhibited a higher appreciation rate than the other countries, the strong relationship between the cryptocurrency market cap growth rate and the USD appreciation rate could indicate that the USD isn't just strengthening, but other global currencies are weakening. This is strongly supported by the INR and EUR consistently having the most negative relationship with the cryptocurrency market growth rate.

The inflation rate was the only variable that consistently showed a statistically insignificant relationship with the cryptocurrency market cap growth rate. However, the interest rates exhibited a strongly negative relationship, even when it was not statistically significant with the FE model. This lines up very well with traditional economic theory, as lower interest rates are typically used to stimulate demand and growth by encouraging borrowing and spending. Therefore, low interest rates might mean investors have access to more capital at a cheaper cost of borrowing, and therefore more capital to invest into assets such as cryptocurrencies.

Across all three models, the Shock variable had a strongly negative relationship with the market cap growth, even though it was only statistically significant in the RE model. This indicates that the years which had macroeconomic shocks were very negatively impacted by them, especially in terms of the cryptocurrency market growth.

Figure 2: Regression without 2018 Shock Coefficient plot

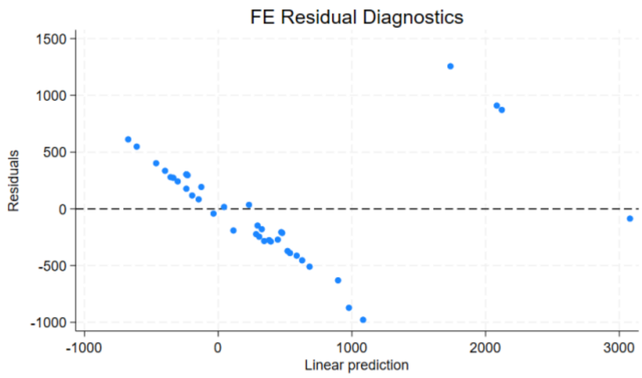


The 2020 COVID-19 pandemic and the 2022 Ukraine invasion were much larger scales than the 2018/19 China-US trade war. Therefore, I also ran some regressions and other diagnostic tests without the 2018 and 2019 Macroeconomic Shock. I excluded the POLS model because of the strong multicollinearity (as shown with the correlation matrix below).

Once again, the USD conversion percentage change and GDP growth rate had the largest positive impact. The INR and EUR conversion rates percentage change still had a negative relationship, and the interest rates still had a strongly negative relationship, with the RE model being the only statistically significant coefficient.

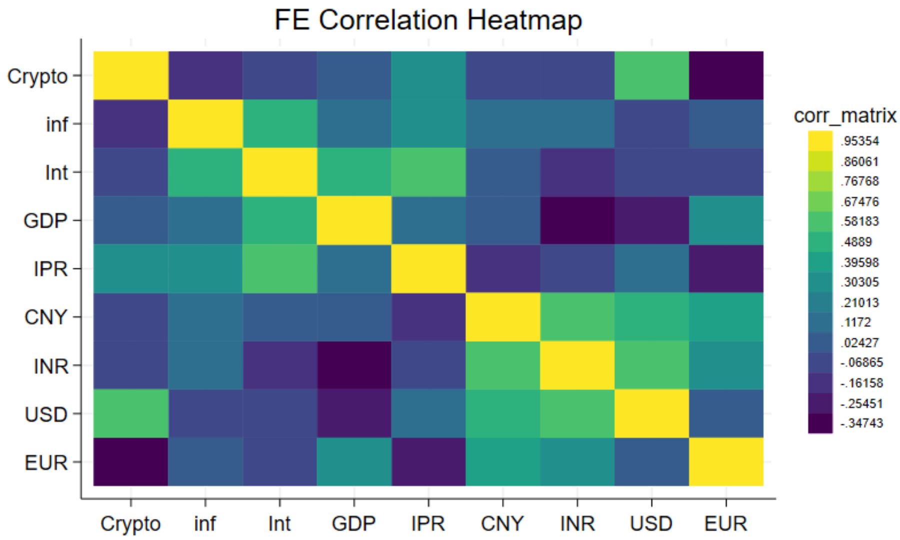
However, quite notably, with this change the relationship with the inflation rates was less strongly positive, and the relationship with the shock variable was considerably more strongly positive. Though none of these changes made the variables coefficients statistically significant, it did indicate that the economic turmoil in 2020 and 2022 might have contributed to more cryptocurrency growth, however it is very uncertain due to the large standard error.

Figure 3: FE without 2018 Shock Residuals vs Fitted Values Plot



I plotted a graph for the FE estimates model of the residuals against the fitted values. The points show a clear negative trend, strongly indicating the presence of heteroscedasticity. As the cryptocurrency market cap increases over time, the market's volatility also increases as the asset becomes more speculative. Consequently, this can lead to a very high error between the predicted value and the observed values.

Figure 4: Correlation Heatmap



I also plotted a correlation matrix of all the variables and converted it to a heat map. This not only showed the same trends that the coefficients of the variables showed, it also showed the relationship between the variables. Variables such as the interest rates and inflation rate showed a particularly high correlation. This is to be expected as high interest rates are set with the intention of combating high inflation rates. However, there were also several strong correlations between the exchange rates. Once again, while high multicollinearity negatively impacts regression models, in this instance, including all the variables also uncovered several key factors that might influence the cryptocurrency market's growth rate.

Figure 5: POLS Regression with 2018 Shock Data Table

```
. reg Crypto inf Int GDP IPR CNY INR USD EUR Shock i.Country i.Year, cluster(Country)
note: 2022.Year omitted because of collinearity.

Linear regression                               Number of obs     =         40
                                                F(1, 3)           =          .
                                                Prob > F          =          .
                                                R-squared         =     1.0000
                                                Root MSE          =          0

                                  (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
inf	1.56e-12	1.79e-12	0.87	0.448	-4.15e-12	7.27e-12
Int	-2.34e-12	2.20e-12	-1.07	0.365	-9.33e-12	4.65e-12
GDP	-6.84e-13	1.42e-12	-0.48	0.663	-5.20e-12	3.83e-12
IPR	3.93e-13	4.85e-13	0.81	0.477	-1.15e-12	1.94e-12
CNY	8.26e-12	8.43e-12	0.98	0.400	-1.86e-11	3.51e-11
INR	3.25e-12	2.92e-12	1.11	0.346	-6.03e-12	1.25e-11
USD	1.31e-11	1.30e-11	1.01	0.387	-2.83e-11	5.45e-11
EUR	-2.44e-11	2.23e-11	-1.09	0.354	-9.55e-11	4.66e-11
Shock	1.329998	2.17e-10	6.1e+09	0.000	1.329998	1.329998
Country						
2	-1.04e-12	4.67e-12	-0.22	0.838	-1.59e-11	1.38e-11
3	-3.31e-12	3.63e-12	-0.91	0.429	-1.48e-11	8.23e-12
4	-1.72e-11	1.62e-11	-1.06	0.367	-6.87e-11	3.43e-11
Year						
2015	128.77	5.64e-11	2.3e+12	0.000	128.77	128.77
2016	209.17	2.47e-10	8.5e+11	0.000	209.17	209.17
2017	3055.05	4.68e-10	6.5e+12	0.000	3055.05	3055.05
2018	-16.11	1.02e-11	-1.6e+12	0.000	-16.11	-16.11
2019	121.44	2.65e-11	4.6e+12	0.000	121.44	121.44
2020	327.02	2.09e-10	1.6e+12	0.000	327.02	327.02
2021	236.11	6.88e-11	3.4e+12	0.000	236.11	236.11
2022	0	(omitted)				
2023	167.77	3.53e-10	4.8e+11	0.000	167.77	167.77
_cons	-61.71	2.69e-10	-2.3e+11	0.000	-61.71	-61.71

Figure 6: POLS Regression with 2018 Shock VIF results

Variable	VIF	1/VIF
inf	4.86	0.205776
Int	13.14	0.076106
GDP	8.80	0.113598
IPR	3.68	0.271672
CNY	566.52	0.001765
INR	408.04	0.002451
USD	675.91	0.001479
EUR	884.21	0.001131
Shock	932.99	0.001072
Country		
2	5.55	0.180122
3	4.95	0.201826
4	8.67	0.115377
Year		
2015	25.66	0.038970
2016	341.51	0.002928
2017	1013.46	0.000987
2018	26.83	0.037266
2019	107.01	0.009345
2020	560.23	0.001785
2021	56.62	0.017661
2023	554.46	0.001804
Mean VIF	310.16	

Figure 7: FE Regression with 2018 Shock Data Table

```
. xtreg Crypto inf Int GDP IPR CNY INR USD EUR Shock, fe cluster(Country)

Fixed-effects (within) regression               Number of obs     =         40
Group variable: Country                         Number of groups  =          4

R-squared:                                      Obs per group:
     Within  = 0.7529                                         min =         10
                                                              avg =       10.0
     Overall = 0.7335                                         max =         10

                                                F(3, 3)           =          .
corr(u_i, Xb) = -0.1603                         Prob > F          =          .

                                  (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
inf	18.50171	19.69667	0.94	0.417	-44.18187	81.1853
Int	-146.3695	97.07556	-1.51	0.229	-455.3072	162.5683
GDP	118.5516	12.4346	9.53	0.002	78.9792	158.1241
IPR	55.53652	9.969787	5.57	0.011	23.80821	87.26483
CNY	-1.487684	16.96037	-0.09	0.936	-55.46316	52.48779
INR	-48.11524	11.35671	-4.24	0.024	-84.25736	-11.97312
USD	126.7125	11.56283	10.96	0.002	89.91445	163.5106
EUR	-71.40638	17.29946	-4.13	0.026	-126.461	-16.35178
Shock	-152.7181	68.45159	-2.23	0.112	-370.5616	65.1254
_cons	436.4529	306.1013	1.43	0.249	-537.6981	1410.604
sigma_u	143.7655					
sigma_e	534.65305					
rho	.06742906	(fraction of variance due to u_i)				

Figure 8: RE Regression with 2018 Shock Data Table

```
. xtreg Crypto inf Int GDP IPR CNY INR USD EUR Shock, re cluster(Country)

Random-effects GLS regression                   Number of obs     =         40
Group variable: Country                         Number of groups  =          4

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         10
     Between = 0.0000                                         avg =       10.0
     Overall = 0.7484                                         max =         10

                                                Wald chi2(3)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                               (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
inf	26.7693	21.0933	1.27	0.204	-14.5728	68.11141
Int	-178.5396	31.07899	-5.74	0.000	-239.4533	-117.6259
GDP	107.0545	18.45808	5.80	0.000	70.87735	143.2317
IPR	50.5589	5.32265	9.50	0.000	40.1267	60.99111
CNY	5.124484	6.239379	0.82	0.411	-7.104475	17.35344
INR	-56.17833	12.99708	-4.32	0.000	-81.65213	-30.70452
USD	130.2727	9.634954	13.52	0.000	111.3885	149.1569
EUR	-68.5113	16.62868	-4.12	0.000	-101.1029	-35.91969
Shock	-152.4533	63.458	-2.40	0.016	-276.8287	-28.07793
_cons	572.9967	51.44106	11.14	0.000	472.1741	673.8193
sigma_u	0					
sigma_e	534.65305					
rho	0	(fraction of variance due to u_i)				

Figure 9: POLS Regression without 2018 Shock Data Table

```
. reg Crypto inf Int GDP IPR CNY INR USD EUR Shock i.Country i.Year, cluster(Country)
note: 2022.Year omitted because of collinearity.

Linear regression                               Number of obs     =         40
                                                F(0, 3)           =          .
                                                Prob > F          =          .
                                                R-squared         =     1.0000
                                                Root MSE          =          0

                                  (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
inf	2.38e-12	2.60e-12	0.92	0.427	-5.89e-12	1.07e-11
Int	-3.43e-12	3.20e-12	-1.07	0.362	-1.36e-11	6.74e-12
GDP	-1.03e-12	2.05e-12	-0.50	0.649	-7.55e-12	5.49e-12
IPR	5.79e-13	7.10e-13	0.81	0.475	-1.68e-12	2.84e-12
CNY	7.88e-12	8.89e-12	0.89	0.441	-2.04e-11	3.62e-11
INR	5.21e-12	4.51e-12	1.16	0.331	-9.13e-12	1.96e-11
USD	2.05e-11	1.94e-11	1.06	0.369	-4.13e-11	8.23e-11
EUR	-3.33e-11	3.07e-11	-1.09	0.356	-1.31e-10	6.42e-11
Shock	1.329998	2.86e-10	4.7e+09	0.000	1.329998	1.329998
Country						
2	-1.60e-12	6.48e-12	-0.25	0.821	-2.22e-11	1.90e-11
3	-4.54e-12	5.24e-12	-0.87	0.450	-2.12e-11	1.21e-11
4	-2.45e-11	2.29e-11	-1.07	0.364	-9.74e-11	4.85e-11
Year						
2015	128.77	7.22e-11	1.8e+12	0.000	128.77	128.77
2016	209.17	3.26e-10	6.4e+11	0.000	209.17	209.17
2017	3055.05	6.57e-10	4.7e+12	0.000	3055.05	3055.05
2018	-14.78	3.00e-10	-4.9e+10	0.000	-14.78	-14.78
2019	122.77	3.17e-10	3.9e+11	0.000	122.77	122.77
2020	327.02	3.18e-10	1.0e+12	0.000	327.02	327.02
2021	236.11	1.03e-10	2.3e+12	0.000	236.11	236.11
2022	0	(omitted)				
2023	167.77	4.82e-10	3.5e+11	0.000	167.77	167.77
_cons	-61.71	3.73e-10	-1.7e+11	0.000	-61.71	-61.71

Figure 10: FE Regression without 2018 Shock Data Table

```
. xtreg Crypto inf Int GDP IPR CNY INR USD EUR Shock, fe cluster(Country)

Fixed-effects (within) regression               Number of obs     =         40
Group variable: Country                         Number of groups  =          4

R-squared:                                      Obs per group:
     Within  = 0.7598                                          min =         10
                                                               avg =       10.0
     Overall = 0.6982                                          max =         10

                                                F(3, 3)           =          .
corr(u_i, Xb) = -0.2848                         Prob > F          =          .

                                (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
inf	-14.88247	34.21023	-0.44	0.693	-123.7547	93.98975
Int	-111.7102	113.1597	-0.99	0.396	-471.8348	248.4144
GDP	142.3712	16.62426	8.56	0.003	89.46542	195.2771
IPR	60.138	10.06415	5.98	0.009	28.10938	92.16662
CNY	8.874696	18.32839	0.48	0.661	-49.45441	67.2038
INR	-90.05993	5.756398	-15.65	0.001	-108.3794	-71.7405
USD	145.3402	11.19831	12.98	0.001	109.7021	180.9782
EUR	-57.49131	21.33465	-2.69	0.074	-125.3877	10.40507
Shock	433.9891	251.9296	1.72	0.183	-367.7634	1235.742
_cons	261.2274	322.0584	0.81	0.477	-763.7061	1286.161
sigma_u	264.26799					
sigma_e	527.08962					
rho	.20087833	(fraction of variance due to u_i)				

Figure 11: RE Regression without 2018 Shock Data Table

```
. xtreg Crypto inf Int GDP IPR CNY INR USD EUR Shock, re cluster(Country)

Random-effects GLS regression                   Number of obs     =         40
Group variable: Country                         Number of groups  =          4

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         10
     Between = 0.0000                                         avg =       10.0
     Overall = 0.7502                                         max =         10

                                                Wald chi2(3)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                               (Std. err. adjusted for 4 clusters in Country)
```

Crypto	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
inf	15.12474	30.09681	0.50	0.615	-43.86392	74.1134
Int	-177.9393	34.14226	-5.21	0.000	-244.8569	-111.0217
GDP	114.3621	16.73578	6.83	0.000	81.56056	147.1636
IPR	51.48997	5.997613	8.59	0.000	39.73487	63.24508
CNY	15.79129	5.569347	2.84	0.005	4.875575	26.70702
INR	-93.19947	8.046292	-11.58	0.000	-108.9699	-77.42903
USD	146.6766	9.639614	15.22	0.000	127.7833	165.5699
EUR	-56.67118	20.3045	-2.79	0.005	-96.46727	-16.87509
Shock	242.4523	172.3441	1.41	0.159	-95.33596	580.2406
_cons	531.3374	61.17923	8.68	0.000	411.4283	651.2465
sigma_u	0					
sigma_e	527.08962					
rho	0	(fraction of variance due to u_i)				

Figure 12: Breush Pagan Test:

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        Crypto[Country,t] = Xb + u[Country] + e[Country,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                  Crypto |   800772.6        894.859
                       e |   277823.5       527.0896
                       u |          0              0

        Test: Var(u) = 0
                             chibar2(01) =     0.00
                          Prob > chibar2 =   1.0000
```

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