Dominant Settlement Currencies in DeFi

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Abstract

Abstract Using DeFi as an experiment, we examine several hypotheses for dominant currencies.XXX

JEL classification codes: D86, G01, G30.

Keywords: Cross-border payment charges, Network, Peer effect, Trading invoicing and Settlement currencies

1 Introduction

Give some introduction here.

The paper is structured as follows: in sec:datamethod we illustrates the format and method of the sample data.

2 Dominant Currency Hypotheses

There is a large international trade literature on the dominant currency. Several mechanisms have been proposed to explain how certain currencies (e.g., pound in the past or dollar in the current period) have been chosen as the dominant currencies for trade invoicing and settlements. Interestingly, the competition for the status of dominant currency has also been played out in the parallel virtual economy since the start of the blockchain technology in 2009. There are several crypto currencies have been used for settlement purposes and there is no clear dominance yet partly due to rapid technological shocks. This setting offers an ideal lab to examine whether any of the proposed mechanisms in the international trade literature are relevant to explain the rise of dominant currencies and how. In the rest of this section, we develop testable hypotheses based on the theoretical findings in the existing literature and construct specifications for these tests.

Intuitively, a currency is most likely to be chosen as the settlement currency if its real purchasing power is stable. Indeed, in the trade literature, this (in-)stability is captured by the bilateral exchange rate volatility between the invoicing currency for exports and the currency used for purchasing the consumption goods (which can be either local currency or the currency used to pay for imported consumption goods). Since the real consumption is denominated in dollars, a measure of purchasing power volatility is, therefore, the volatility of crypto currency in dollars,. This leads to our first testable hypothesis.

Hypothesis 1 (dollar volatility): A crypto currency is more likely to be used as a settlement currency when the volatility of its exchange rate with dollar, denoted by volatility$_dollar, islower.$

Furthermore, in the trade literature,[5] have pinpointed that the special roles played by the safe asset – the currency that is regarded as "stable" in maintaining its real value and hence is used as deposits and collateral for borrowing – give rise to its role as the settlement asset. This indicates that, in addition to lower volatility, traders might prefer the price stability of stablecoins when choosing a settlement asset, which leads to the following variation of Hypothesis 1.

Hypothesis 1A (Stablecoins): Stablecoins are more likely to be used a settlement assets, especially during the volatile period.

However, the trade literature also shows that firms are more concerned about currency mismatch between export sales denominated in the invoicing currency and the working capital denominated in local currency, instead of the purchasing power of the export sales for consumption goods directly. In this case, the bilateral exchange rate volatility with the currency used to pay for working capital might be an important consideration for firms to choose the currency for export invoices. This mechanism is proposed by [1]. Similar ideas are also in [8], [6] and [5]. In the blockchain environment, working capital is denominated in the utility coin associated with a specific chain. For example, on the Etherum blockchain, each transaction has to pay a gas fee (akin to working capital) priced in ETH. This means that the bilateral exchange rate volatility with ETH might be an important consideration for choosing an invoicing currency. This leads to our second testable hypothesis.

Hypothesis 2 (ETH volatility): A crypto currency is more likely to be chosen as a settlement currency when the volatility of its exchange rate with ETH, denoted by volatility$_ETH, islower$.

Alternatively,[4] find that network effect might explain why certain currencies are dominant. They argue that firms in country i have a preference to invoice their exports in the same currency as the countries from which they import from. This is to minimize the currency mismatch on their assets and liabilities. Network effects lead to certain currencies such as dollar emerging as the dominant currency for countries to coordinate on currencies to invoice their trades. In the crypto setting, the network effect can be proxied by the market capitalization and the age of the cryto assets. For example, Bitcoin, one of the oldest and the most widely held crypto assets, has a market capitalization of $411.41 billionasofAugust 2022, whichdoublesthatofEtheruminthesecondplaceandfivetimesthatofUSDC$

Hypothesis 3 (network effects): A crypto currency that has a larger network of investors is more likely to be chosen as a settlement currency.

Lastly, [8], [6] and [5] suggest that exporting and importing firms have incentive to invoice in currencies that are associated with higher levels of financial services. If there is a well developed debt/credit/derivative market denominated in a certain currency, which means that trade financing, work capital financing, banking services, and currency risk hedging in that particular currency would be cheaper and readily available. Financial service applications such as deposit, lending, investing, hedging, insurance, etc in the crypto universe have only been developed in the last three years when blockchains developers started making use of the smart contract functionality. These applications are characterized as decentralized finance since they are provided preserving anonymity, algorithmic-based and without any centralized authority. We use several measures of the level of financial services associated with each crypto currency: total amount of deposit, total amount of borrowing, total value locked in Defi other than Uniswap.

Hypothesis 4 (financial service): A currency with more traded financial products is more likely to be chosen as a settlement currency.

In the next section, we develop specifications to test these hypotheses both cross-sectionally and time-series wise. More importantly, we aim to examine under what circumstances certain mechanisms making dominance currency are more relevant. For example, it is possible, stablecoins are major dominant currencies during the volatile time, while utility coins such as ETH provide better settlement service during the high fee period. It is also possible, during the crypto market booms, more currencies provide settlement services while the opposite happen during the market bust.

3 Data and Method

The dataset is composed of data from several platforms, including Uniswap V2, Uniswap V3, AAVE, Compound, Ethereum Network, and the cryptocurrency market. Data acquisition methods are listed in Table 1.

Table 1: Data Sources and Acquisition

Platform	Acquisition API	Introduction
Uniswap V2	Uniswap V2 Subgraph API	DEX, Exchange
Uniswap V3	Uniswap V3 Subgraph API	DEX, Exchange
Compound	Compound Finance API	DEX, Defi Lending
AAVE	Dune Analytics (non-official)	DEX, Defi Lending
Ethereum Network	Etherscan API, Infura API	Network
Cryptocurrency Market	CoinGecko	Global Market

The observation horizon starts from May 18, 2020, when Uniswap V2 formally launched, until June 1, 2022. For comparison, Uniswap V3 was introduced after May 5, 2021. The main observation objects are the top 50 pools of the two versions of Uniswap protocol, which are determined by average daily trading volume USD of each month.

(TBD: data sample overview)

The lists of all Uniswap V2 and Uniswap V3 liquidity pools are fetched from the original factory contract by Uniswap V2 Subgraph API and V3 Subgraph API respectively. The data sample comprises 84,101 individual liquidity pools, consisting of 77,014 V2 pools and

7,087 V3 pools until June 24, 2022. In total, the sample contains 97,293,787 transactions on Uniswap, including 80,845,450 transactions in V2 and 16,448,337 transactions in V3, from its inception on May 5, 2020 and May 4, 2021 separately until June 24, 2022.

(TBD: only have top 50 pools) Specifically, We observe XXX liquidity injection, xxx withdrawal, xxxx trades.

(TBD: token overview)

Volume

The volume data can be directly fetched by the Subgraph APIs as USD derived via ETH prices from the tokens within the whitelist [7]. Besides, the volume USD can also be manually computed. For the pools trade against WETH, the WETH part of the trade can be taken and converted to USD using UNISWAP dollar price feed of WETH (or from the WETH/stablecoin pool with the highest volume). For the majority of the remaining pools which trade against a USD stablecoin, the volume could be converted by the stablecoin part. For all remaining pools we search for all pools where one of the tokens trades against WETH and convert it using the prices from the pool with the highest volume.

Pool size

(TBD) We need find total LP coins issued in each pool.

Gas fee

The historical data of daily average gas fee of Ethereum is downloaded from Etherscan, which presents the gas fee in the unit of Wei [3]. Furthermore, the historical data of Ether daily price in USD is also provided by Etherscan, so that the gas fee can be converted as the unit of USD [2].

3.1 Measuring dominant currency

3.2 Eigenvector centrality

For this exercise we pick the top 50 pools (we need to decide the cutoff by visually inspecting the gross volume of pools to see if there is a clear cutoff). For each day, we first compute directional bilateral volume (say WETH to DAI or DAI to WETH) and map out the network graph (standard network visualization diagram tool exists where the link if the volume (directional or gross) and size of the node is the sum of size of the pools a coin is in.

Eigenvector centrality is computed by function: eigenvector_centrality_numpy of NetworkX python package after plotting the network graph. It computes the centrality for a node, which indicates one token among top 50 pools, based on the centrality of its neighbors as the formula for node i:

$$Ax = \lambda x$$

where A is the adjacency matrix of graph G with eigenvalue λ. Hence, there is a unique positive solution if λ is the highest value based on the virtue of the Perron–Frobenius theorem [9].

The measurement is introduced by Phillip [11]. Since directed graph is used in the plot, the default setting generates "left" eigenvector centrality corresponding with in-edges of the graph. While out-edges eigenvector centrality requires the reverse of the graph. This function solve the solution by using SciPy sparse eigenvalue solver (ARPACK) to get the largest eigenvector pair [10].

Compute inflow and outflow eigenvalue centrality, and gross centrality. Map top five key coins over time.

3.3 Variables

Variables and definitions are in Table 2.

Table 2: Definitions and Descriptions of Variables

Variable	Descriptions
eigencentrality_in	eigenvector centrality calculated by inflow trade volume
eigencentrality_out	eigenvector centrality calculated by outflow trade volume
inflow_volume	daily total inflow volume USD involved in top50 pools
outflow_volume	daily total outflow volume USD involved in top50 pools
price	price of cryptocurrency on global market
price_vol	volatility of asset price by daily log return and rolling 30 days standard deviatio
market_cap	market capitalization of cryptocurrency on global market
gas_price	daily average gas price (converted to USD by ETH close price) of Ethereum netwo
gas_vol	volatility of gas fee by daily log result and rolling 30 days standard deviation
defi_deposit	sum of total deposit (supply) USD of AAVE and Compound
defi_borrow	sum of total borrow USD of AAVE and Compound

3.4 Explaining dominance

Dominance is mainly measured using eigenvector centrality. We can also use pool size: that is, for each coin, we sum the sizes of all the pools it is in – this is akin to the size of the node in the network graph.

To test the hypotheses we run the following regression analysis to see which variables explain the dominant currency well.

$$\text{centrality}_{it} = a_t + a_i + b_1\text{fee} + b_1\text{vol}_{fee} + \sum_j b_{2j} DeFi_j + \sum_j b_{3j} vol_j + b_4\text{vol}_{in} + b_5\text{vol}_{out} + \epsilon_{it}$$

3.4.1 Gas fee

This is about transaction cost, measured by the level of gas and volatility of gas fee. In this case, all dominant currencies have to pay this transaction cost since UNISWAP is on the Etherum. We can examine, by structure break, to see whether in the low fee period, there is (relatively) frequent switch between dominant currencies.

3.4.2 Financial development

DeFi borrowing and lending in the invoice currency denoted by j (check TVL in each coin in DeFi lending platforms compound and aave)

3.5 Volatility of invoice currencies

Invoice currency include: WETH WBTC

3.6 Volatility of in-degree or out-degree coin

If stablecoins are the invoice currency, correlation between in-degree (out-degree) coin with stablecoin, weighted by the (directional) volume of trades between stablecoins and these coins. Basically this is the dollar volatility of these coins weighted by trading volume with stable coins. Here we treat all stablecoins the same. We could separate this volatility measures for the algorithm stable coins, custodian stablecoins, and DAI.

3.7 Market microstructure

Price impact, reversal trade (asymmetric info), number of trades (not dollar volume) might matter as well. This is about market design.

Empirical Methodology Estimation Results

4 Conclusion

Conclusion here.

References

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A Appendix,V2

B Appendix,V3

Table 3: Independent Variable Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
gas_price	15,709	0.0003	0.0002	0.00002	0.0001	0.0004	0.001
gas_price_volatility	15,709	5.421	2.164	2.644	3.804	6.026	12.568
price	8,880	2,866.500	10,326.880	0.00000	0.999	26.308	82,070.760
price_volatility	8,879	1.860	4.807	0.012	0.130	1.729	50.640
mcap	8,880	9,966,820,197.000	17,660,137,434.000	0.000	260,404,038.000	10,097,052,724.000	83,424,696,945.000
borrow_compound	15,709	142,415,470.000	564,636,904.000	0	0	0	4,222,933,465
lend_compound	15,709	317,027,279.000	1,037,107,734.000	0	0	0	7,689,121,633
borrow_aave	15,709	140,904,669.000	541,813,796.000	0	0	6,077,481.0	5,298,214,989
lend_aave	15,709	344,182,212.000	995,766,707.000	0	0	49,063,836.0	9,059,265,993

Table 4: Correlation of Independent Variables

	gas_price	gas_price_volatility	price	price_volatility	mcap	borrow_compound	lend_compound	borrow_aave	lend_aave
gas_price	1	-0.411	0.039	-0.020	0.041	0.087	0.095	0.048	0.067
gas_price_volatility	-0.411	1	-0.001	0.072	-0.028	-0.064	-0.068	-0.025	-0.043
price	0.039	-0.001	1	-0.054	-0.014	-0.091	-0.050	-0.071	0.165
price_volatility	-0.020	0.072	-0.054	1	-0.158	-0.120	-0.107	-0.127	-0.138
mcap	0.041	-0.028	-0.014	-0.158	1	0.305	0.357	0.461	0.449
borrow_compound	0.087	-0.064	-0.091	-0.120	0.305	1	0.729	0.843	0.546
lend_compound	0.095	-0.068	-0.050	-0.107	0.357	0.729	1	0.649	0.878
borrow_aave	0.048	-0.025	-0.071	-0.127	0.461	0.843	0.649	1	0.666
lend_aave	0.067	-0.043	0.165	-0.138	0.449	0.546	0.878	0.666	1

Table 5: Correlation of Dependent Variables

	eigencentrality_in	eigencentrality_out	trading_volume_total	total_tvl
eigencentrality_in	1	0.996	0.883	0.897
eigencentrality_out	0.996	1	0.882	0.896
trading_volume_total	0.883	0.882	1	0.833
total_tvl	0.897	0.896	0.833	1

Table 6: Dependent Variable Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
eigencentrality_in	15,709	0.056	0.160	−0	0.001	0.01	1
eigencentrality_out	15,709	0.056	0.160	−0	0.001	0.01	1
trading_volume_total	15,709	77,293,235.000	266,681,682.000	0	1,262,046.0	11,666,074.0	3,784,529,192
total_tvl	15,709	135,213,949.000	360,671,853.000	0	4,616,085.0	35,245,234.0	2,894,255,967

Table 7: Summary Statistics by groups

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Stable Coins:							
eigencentrality_in	4,270	0.107	0.203	−0.000	0.002	0.104	0.723
eigencentrality_out	4,270	0.107	0.204	−0.000	0.002	0.104	0.715
trading_volume_total	4,270	136,145,564.000	308,293,595.000	0.000	2,163,998.000	103,252,754.000	3,355,691,900.000
total_tvl	4,270	270,510,856.000	478,076,617.000	0.000	10,070,567.000	336,410,010.000	2,894,255,967.000
WETH:							
eigencentrality_in	453	0.692	0.024	0.595	0.678	0.708	0.757
eigencentrality_out	453	0.689	0.028	0.447	0.675	0.707	0.756
trading_volume_total	453	1,134,356,631.000	531,089,434.000	7,889,111.000	785,418,012.000	1,334,636,112.000	3,784,529,192.000
total_tvl	453	1,399,261,097.000	363,511,383.000	64,269,546.000	1,161,705,491.000	1,712,462,714.000	1,991,978,002.000
Others:							
eigencentrality_in	34,322	0.029	0.056	−0.000	0.005	0.029	0.723
eigencentrality_out	34,322	0.029	0.053	−0.000	0.006	0.029	0.719
trading_volume_total	34,322	3,775,610.000	14,196,831.000	0.000	442,683.100	3,394,121.000	1,345,104,084.000
total_tvl	34,322	18,649,699.000	254,484,003.000	0.000	1,872,936.000	14,394,487.000	46,402,313,545.000

Table 8: Regression Result

	Dependent variable:			
	eigencentrality_in			
	(1)	(2)	(3)	(4)
price	0.100***	0.101***	−0.142***	−0.158***
	(0.008)	(0.009)	(0.044)	(0.048)
price_volatility	0.007	0.007	0.018	0.015
	(0.014)	(0.017)	(0.017)	(0.018)
mcap	0.451***	0.450***	0.027	0.008
	(0.009)	(0.011)	(0.125)	(0.142)
gas_price	−0.005	−0.002	0.025	0.001
	(0.009)	(0.016)	(0.020)	(0.013)
gas_price_volatility	0.017*	0.017	0.004	0.010
	(0.009)	(0.011)	(0.014)	(0.012)
borrow_total_relative	0.007	0.005	−0.008	−0.003
	(0.168)	(0.201)	(0.040)	(0.052)
lend_total_relative	−0.003	0.0002	0.007	0.003
	(0.166)	(0.198)	(0.039)	(0.051)
Dummy_WETH1	3.850***	3.854***		
	(0.036)	(0.043)	(0.000)	(0.000)
Dummy_Stable	0.697***	0.704***		
	(0.022)	(0.026)	(0.000)	(0.000)
SnP		−0.00000		0.00003
		(0.00001)		(0.00002)
gas_price:Dummy_WETH1	−0.128***	−0.133***	−0.014	−0.009
	(0.039)	(0.046)	(0.023)	(0.027)
gas_price_volatility:Dummy_WETH1	0.027	0.017	−0.011	−0.016
	(0.037)	(0.045)	(0.016)	(0.016)
Constant	−0.134***	−0.121**		
	(0.011)	(0.056)		
Crypto Index Control	No	Yes	No	Yes
Fixed effects	-	-	Token	Token
Observations	7,934	5,656	7,934	5,656
R^2	0.706	0.705	0.976	0.977
Adjusted R^2	0.706	0.704	0.976	0.977
Residual Std. Error	0.723 (df = 7922)	0.725 (df = 5643)	0.206 (df = 7891)	0.203 (df = 5612)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Regression Result

	Dependent variable:			
	eigencentrality_out			
	(1)	(2)	(3)	(4)
price	0.103***	0.105***	−0.132***	−0.135***
	(0.008)	(0.009)	(0.042)	(0.041)
price_volatility	0.007	0.007	0.018	0.017
	(0.014)	(0.017)	(0.016)	(0.018)
mcap	0.453***	0.451***	0.029	0.018
	(0.009)	(0.011)	(0.120)	(0.136)
gas_price	−0.003	−0.0004	0.027	0.002
	(0.009)	(0.016)	(0.020)	(0.016)
gas_price_volatility	0.018*	0.016	0.005	0.010
	(0.009)	(0.011)	(0.014)	(0.013)
borrow_total_relative	0.004	0.0004	−0.012	−0.012
	(0.168)	(0.201)	(0.039)	(0.050)
lend_total_relative	0.001	0.005	0.012	0.013
	(0.166)	(0.198)	(0.038)	(0.049)
Dummy_WETH1	3.828***	3.841***		
	(0.037)	(0.043)	(0.000)	(0.000)
Dummy_Stable	0.701***	0.708***		
	(0.022)	(0.026)	(0.000)	(0.000)
SnP		−0.00000		0.00003
		(0.00001)		(0.00002)
gas_price:Dummy_WETH1	−0.148***	−0.154***	−0.034	−0.033
	(0.039)	(0.046)	(0.022)	(0.026)
gas_price_volatility:Dummy_WETH1	0.028	0.027	−0.009	−0.005
	(0.038)	(0.045)	(0.017)	(0.017)
Constant	−0.133***	−0.127**		
	(0.011)	(0.056)		
Crypto Index Control	No	Yes	No	Yes
Fixed effects	-	-	Token	Token
Observations	7,934	5,656	7,934	5,656
R^2	0.703	0.704	0.976	0.975
Adjusted R^2	0.703	0.703	0.975	0.975
Residual Std. Error	0.726 (df = 7922)	0.726 (df = 5643)	0.209 (df = 7891)	0.210 (df = 5612)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Regression Result

	Dependent variable:			
	trading_volume_total			
	(1)	(2)	(3)	(4)
price	0.062***	0.071***	−0.166***	−0.142***
	(0.009)	(0.011)	(0.055)	(0.051)
price_volatility	0.003	0.006	0.055	0.061
	(0.016)	(0.020)	(0.055)	(0.064)
mcap	0.364***	0.403***	0.437*	0.565**
	(0.011)	(0.013)	(0.226)	(0.242)
gas_price	0.029***	0.109***	0.043*	0.110**
	(0.011)	(0.020)	(0.022)	(0.050)
gas_price_volatility	0.012	−0.002	0.013	0.008
	(0.011)	(0.014)	(0.012)	(0.014)
borrow_total_relative	0.029	0.018	−0.060	−0.111
	(0.196)	(0.245)	(0.071)	(0.103)
lend_total_relative	−0.022	−0.010	0.060	0.106
	(0.193)	(0.241)	(0.069)	(0.098)
Dummy_WETH1	3.902***	4.191***		
	(0.043)	(0.053)	(0.000)	(0.000)
Dummy_Stable	0.518***	0.557***		
	(0.026)	(0.032)	(0.000)	(0.000)
SnP		−0.0001***		−0.0001*
		(0.00002)		(0.0001)
gas_price:Dummy_WETH1	0.506***	0.457***	0.486***	0.413***
	(0.045)	(0.056)	(0.081)	(0.086)
gas_price_volatility:Dummy_WETH1	0.043	0.099*	0.046*	0.103***
	(0.044)	(0.055)	(0.025)	(0.022)
Constant	−0.127***	0.283***		
	(0.012)	(0.068)		
Crypto Index Control	No	Yes	No	Yes
Fixed effects	-	-	Token	Token
Observations	7,934	5,656	7,934	5,656
R^2	0.612	0.629	0.787	0.811
Adjusted R^2	0.612	0.629	0.785	0.810
Residual Std. Error	0.844 (df = 7922)	0.885 (df = 5643)	0.628 (df = 7891)	0.634 (df = 5612)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Regression Result

	Dependent variable:			
	total_tvl			
	(1)	(2)	(3)	(4)
price	0.203***	0.205***	0.021	0.089*
	(0.009)	(0.010)	(0.040)	(0.048)
price_volatility	−0.007	−0.001	0.129	0.135
	(0.015)	(0.018)	(0.132)	(0.132)
mcap	0.391***	0.393***	1.208***	1.237***
	(0.010)	(0.012)	(0.469)	(0.431)
gas_price	−0.079***	0.016	−0.107**	0.003
	(0.010)	(0.018)	(0.045)	(0.029)
gas_price_volatility	−0.013	−0.041***	0.020	−0.008
	(0.010)	(0.013)	(0.013)	(0.013)
borrow_total_relative	−0.016	−0.031	−0.320	−0.392
	(0.186)	(0.220)	(0.209)	(0.247)
lend_total_relative	0.030	0.044	0.314	0.379
	(0.184)	(0.217)	(0.203)	(0.237)
Dummy_WETH1	3.440***	3.423***		
	(0.040)	(0.047)	(0.000)	(0.000)
Dummy_Stable	0.908***	0.900***		
	(0.024)	(0.029)	(0.000)	(0.000)
SnP		−0.0001***		−0.0002**
		(0.00002)		(0.0001)
gas_price:Dummy_WETH1	0.161***	0.143***	−0.045	−0.076
	(0.043)	(0.050)	(0.115)	(0.109)
gas_price_volatility:Dummy_WETH1	−0.171***	−0.170***	−0.118**	−0.129***
	(0.042)	(0.049)	(0.047)	(0.039)
Constant	−0.149***	0.317***		
	(0.012)	(0.061)		
Crypto Index Control	No	Yes	No	Yes
Fixed effects	-	-	Token	Token
Observations	7,934	5,656	7,934	5,656
R^2	0.632	0.638	0.895	0.902
Adjusted R^2	0.631	0.637	0.894	0.901
Residual Std. Error	0.804 (df = 7922)	0.796 (df = 5643)	0.431 (df = 7891)	0.416 (df = 5612)

Note: *p<0.1; **p<0.05; ***p<0.01