Value Premium, Network Adoption, and Factor Pricing of Crypto Assets

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Introduction

- Emerging crypto market/asset class
  - Total market cap US **$3 trillion** (Nov 11, 2021)
  - Daily volume US **$100 billion**
- **Risk-return tradeoff**
  - Fundamental characteristics: network adoption. → **Fundamental-related factors**
  - Hybrid nature of crypto. Value as defined in the commodities and currencies. → **Value premium and factor**
- **Token Classification**
  - Utility tokens versus security tokens?
  - International asset pricing —— market segmentations; **segmentation in cryptocurrencies?**

Research Questions and Main Findings

Crypto anomalies and in search of a factor model for cross-sectional asset pricing?

Rich dataset on 4,007 cryptocurrencies + fundamental characteristics of 616 cryptocurrencies to study characteristic-based anomalies, construct novel factors, and propose a factor pricing model of crypto assets.

- **Return patterns**
  - Momentum only exits in large cryptocurrencies but not in small ones (reversal in small).
  - Value premium is larger for smaller cryptocurrencies.
  - Network adoption premium exists.
- **A parsimonious five-factor model**
  - Both the LHS approaches (GRS, constrained R^2, absolute value of average alpha, average R^2, cross-sectional R^2) and RHS approaches (spanning, max squared Sharpe); C-5: MKT+SMB+VAL+NET+MOM.

Research Questions and Main Findings

Token classification and market segmentation in cryptocurrencies markets.

Rich dataset on 4,007 cryptocurrencies + fundamental characteristics of 616 cryptocurrencies to study characteristic-based anomalies, construct novel factors, and propose a factor pricing model of crypto assets.

- **Token classification and market segmentation**
  - Manually classify 616 cryptocurrencies into four categories: General Payment Token, Platform Token, Product/Ownership Token, and Security Token
  - We find significant market segmentation among different token categories; the need to use local and international factor models instead of global.

Related Literature

- **Crypto asset pricing**
  - Network effects and user adoption on the valuation:
    - Theoretical: e.g., Cong, Li, and Wang (2021a,b), Sockin and Xiong (2021), Li and Mann (2021), Pagnotta and Buraschi (2018), Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020).
    - Empirical: Shams (2019) measures the network effect using comments posted on “SubReddit” pages; Liu and Tsyvinski (2021) and Bhambhwani, Delikouras and Korniotis (2021) use the growth of the number of addresses of Bitcoin and of ten cryptocurrencies to measure the network effect.
  - Crypto fundamentals and value premium:
    - Valuation ratio cannot predict index returns (Liu and Tsyvinski, 2021)
    - Our contribution: Document a value premium widely observed in various asset classes (Asness, Moskowitz and Pedersen 2013) and demonstrate that the crypto value factor matters for pricing the cross section of cryptocurrencies.
  - Factor models: Liu, Tsyvinski, and Wu (2022), Li and Yi (2019), etc.; momentum effect.
- Our study belongs more broadly to the empirical asset pricing literature, especially characteristic-based anomalies such as momentum and the factor model competition.

The Data

Data Source

Trading Data

Coinmarketcap.com

- Period: 2014/01/01 —— 2021/01/04
- Provides daily data on prices, volume and market capitalization of most cryptocurrencies with information from around 400 exchanges
- Overall, there are 8,378 cryptocurrencies in the sample

Fundamental Data

Intotheblock

- Provides fundamental data on the number of addresses and transaction volume on-chain, etc., but lack of market cap data
- As of 2021/01/04, there are 834 cryptocurrencies on Intotheblock
- After matching the data of Coinmarketcap.com, there are 745 crypto coins

- **Data Clean**
  - Exclude stable coins, coins with zero prices, market capitalization, or trading volumes in all periods.
  - Admitted if no data error in the weekend of the portfolio formation week and the following week.
    - ✓ Errors, for instance, the price or market cap changes with a zero trading volume.

The Data

Final Samples

01

1. **Full Sample**
2. Filter the 8,378 cryptocurrencies from Coinmarketcap.com, our final sample contains 4,007 tokens.

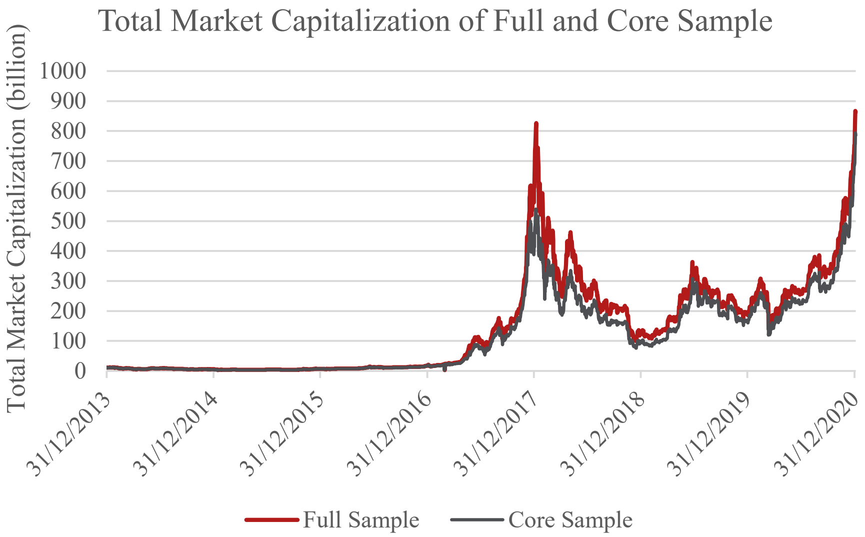
02

1. **LargeCap Sample**
2. To compare with LTW which constrains the sample to only large cap cryptocurrencies, we also construct a separate sample with market value larger than USD 1 million for robustness check.

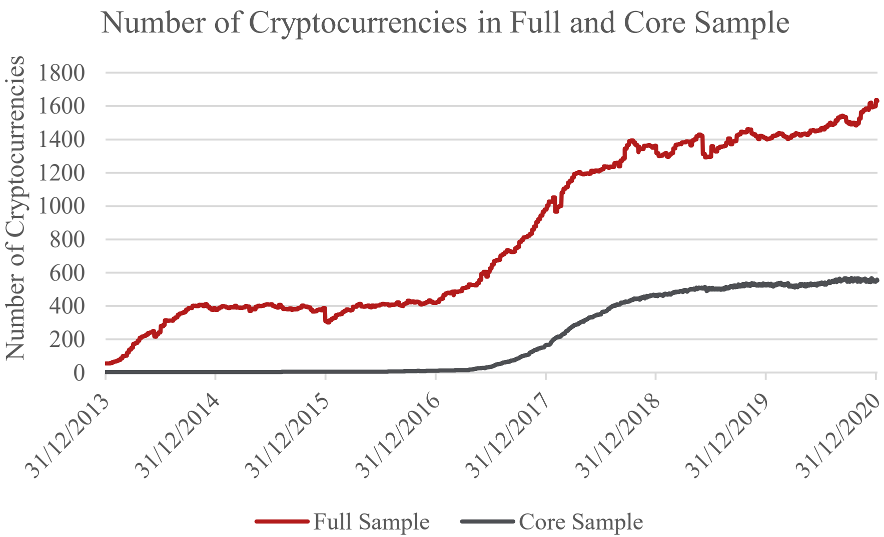
03

1. **Core Sample**
2. Filter the matched 745 cryptocurrencies, there are 616 cryptocurrencies left, containing both trading data and fundamental data.

The Data



Total Market Capitalization of Full and Core Sample
Total Market Capitalization (billion)
1000
900
800
700
600
500
400
300
200
100
0
31/12/2013
31/12/2014
31/12/2015
31/12/2016
31/12/2017
31/12/2018
31/12/2019
31/12/2020
Full Sample
Core Sample



Number of Cryptocurrencies in Full and Core Sample
Number of Cryptocurrencies
1800
1600
1400
1200
1000
800
600
400
200
0
31/12/2013
31/12/2014
31/12/2015
31/12/2016
31/12/2017
31/12/2018
31/12/2019
31/12/2020
Full Sample
Core Sample

Portfolio Returns

- 13 cryptocurrencies characteristics grouped into 4 categories: size, momentum, value and network.
- Single-sorted or double-sorted portfolios at the end of each week and track returns in the following week.

Size Sorted Portfolio Returns

	(1) Full sample										
	1	2	3	4	5	6	7	8	9	10	10-1
MarketCap	**Low**									**High**	
Mean	0.487	0.135	0.100	0.264	0.062	0.046	0.034	0.026	0.011	0.015	-0.471
t(Mean)	3.094	10.355	6.592	1.718	5.591	4.656	3.189	3.043	1.454	2.025	-3.001
	(2) LargeCap Sample										
	Low									**High**	
Mean	0.026	0.026	0.018	0.021	0.015	0.005	0.011	0.005	0.027	0.017	-0.010
t(Mean)	2.496	2.090	1.434	1.564	1.620	0.525	1.133	0.619	2.121	1.806	-0.967

Momentum Sorted Portfolio Returns

	(1) Full sample										
	1	2	3	4	5	6	7	8	9	10	10-1
Momentum	**Low**									**High**	
Mean	0.054	0.012	0.012	0.005	0.006	0.027	0.013	0.031	0.028	0.031	-0.024
t(Mean)	2.044	1.197	1.366	0.543	0.806	2.032	1.877	3.138	2.714	2.159	-0.796
	(2) LargeCap Sample										
	Low									**High**	
Mean	-0.018	0.003	0.008	0.006	0.014	0.022	0.007	0.019	0.022	0.036	0.054
t(Mean)	-1.987	0.311	0.992	0.615	1.522	2.368	1.001	2.328	2.479	2.341	3.357

Panel B: Independent Double Sorts

	Mean						t-statistic					
	Low	2	3	4	**High**	H-L	**Low**	2	3	4	**High**	H-L
Small	0.265	0.106	0.099	0.087	0.072	-0.195	11.996	7.693	6.695	5.269	2.745	-6.043
2	0.460	0.089	0.047	0.050	0.118	-0.343	1.456	4.662	4.224	3.908	1.555	-1.053
3	0.101	0.053	0.067	0.030	0.005	-0.096	9.119	2.899	3.428	3.199	0.511	-8.650
4	0.056	0.027	0.021	0.023	0.010	-0.045	4.901	2.942	2.096	2.096	0.822	-3.300
Big	-0.007	0.004	0.014	0.022	0.034	0.041	-0.692	0.534	2.031	2.960	3.004	3.240

Value Sorted Portfolio Returns

	1	2	3	4	5	6	7	8	9	10	10-1
	(1) Full sample										
Value	**Low**									**High**	
Mean	0.012	0.024	0.009	0.021	0.030	0.016	0.017	0.037	0.036	0.068	0.057
t(Mean)	1.374	2.565	1.328	2.416	2.846	1.531	2.060	3.408	3.904	3.625	3.058
	(2) LargeCap Sample										
	Low									**High**	
Mean	0.012	0.015	0.010	0.019	0.007	0.019	0.025	0.024	0.011	0.030	0.017
t(Mean)	1.178	1.678	1.126	2.120	0.814	1.829	0.161	0.118	1.454	3.066	1.668

Panel B: Independent Double Sorts

	Mean						t-statistic					
	Low	2	3	4	**High**	H-L	**Low**	2	3	4	**High**	H-L
Small	0.044	0.062	0.074	0.178	0.194	0.153	2.736	4.025	5.067	3.884	5.085	4.396
2	0.020	0.065	0.180	0.073	0.113	0.094	1.426	3.696	1.619	5.891	7.149	5.246
3	0.055	0.037	0.080	0.051	0.081	0.026	3.764	3.315	2.940	4.863	6.384	1.749
4	0.014	0.025	0.027	0.035	0.044	0.027	1.449	2.708	2.338	2.778	3.557	2.596
Big	0.018	0.013	0.023	0.019	0.030	0.008	2.281	1.844	2.471	2.132	2.674	0.899

Network Sorted Portfolio Returns

- We measure the network effect of cryptocurrencies using the Core Sample :
- Construct weekly growth rates of fundamental-related characteristics
  - ✓ Changes in total addresses (*TAgrowth*)
  - ✓ Changes in total addresses with balance (*BAgrowth*)
  - ✓ Total transaction volume on-chain (*Volgrowth*)
  - ✓ Total USD transaction volume on-chain (*VolUSDgrowth*).
- BAgrowth and TAgrowth generate statistically significant returns
- Volgrowth and VolUSDgrowth not statistically significant

	Core Sample					
	1	2	3	4	5	5-1
BAgrowth	**Low**				**High**	
Mean	0.008	0.013	0.015	0.018	0.048	0.040
t(Mean)	0.926	1.565	1.561	2.343	3.823	3.221
TAgrowth	**Low**				**High**	
Mean	0.014	0.013	0.021	0.006	0.043	0.028
t(Mean)	1.644	1.373	2.209	1.013	3.247	2.315

The C-5 Model

- Six factor candidates: Market, Size, Momentum, Reversal, Value, and Network.

MKT, SMB, MOM, REV and VAL are constructed by the Full Sample

- **MKT** is the difference between market index (constructed by all available cryptocurrencies in the Full Sample) return and the risk-free interest rate proxied by the 1-month Treasury bill rate.
- The independent 2×3 sort of Full Sample on size (market cap) and value (negative past 52-week return) produce six value-weighted portfolios.
  - ✓ **SMB** is the equal-weighted average of the returns on the three small portfolios minus returns on the three big portfolios.
  - ✓ **VAL** is the equal-weighted average of the return difference of the high and low negative past 52-week return portfolios within small and big groups.
- The independent 2×3 sort of Full Sample on size (market cap) and momentum (past 2-week return) produce six value-weighted portfolios.
  - ✓ **MOM** is the return difference between the highest and the lowest momentum portfolios in the largest size group
  - ✓ **REV** is the return difference in the smallest group

The C-5 Model

- Six factor candidates: Market, Size, Momentum, Reversal, Value, and Network.

NET is constructed by the Core Sample

- Each week we split the cryptocurrencies of the Core Sample into three [30% 40% 30%] groups by the growth rate in total addresses with balance. **NET** is the return difference between the top and the bottom network portfolios.

LTW Benchmark: We construct an alternative market factor, MKT_LTW, size factor, SMB_LTW, and a momentum factor, MOM_LTW using the LargeCap Sample

Selecting Crypto Factors —— A Horse Race of Factor Models

- Fama and French (2018): LHS and RHS approaches.
- **LHS approach**
- Test portfolios: In-Sample test asset portfolios & Out-of-Sample test asset portfolios

  → a total of 150 portfolios of cryptocurrencies

- Competing models: the C-CAPM model, five 3-factor models, three 4-factor models, three 5-factor model, and one 6-factor model

	GRS	p(GRS)	$A\|a\|$	AR^2	R_C^2	$p(R_C)$	Cross R^2
MKT	3.765	0.000	0.036	0.127	-0.029	0.000	0.098
MKT_LTW, SMB_LTW, MOM_LTW	3.700	0.000	0.034	0.161	-0.075	0.000	0.098
MKT, SMB, MOM	3.228	0.000	0.032	0.165	-0.214	0.000	0.081
MKT, SMB, REV	3.244	0.000	0.033	0.181	-0.556	0.000	-0.084
MKT, SMB, VAL	3.102	0.000	0.025	0.177	0.412	0.000	0.578
MKT, SMB, NET	3.315	0.000	0.030	0.164	-0.018	0.000	0.239
MKT, SMB, VAL, MOM	2.922	0.000	0.024	0.184	0.382	0.000	0.554
MKT, SMB, VAL, REV	3.005	0.000	0.031	0.201	-0.486	0.000	-0.030
MKT, SMB, VAL, NET	3.045	0.000	0.024	0.184	0.452	0.000	0.610
MKT, SMB, VAL, MOM, NET	2.880	0.000	0.023	0.192	0.425	0.000	0.588
MKT, SMB, VAL, MOM, REV	2.817	0.000	0.030	0.208	-0.537	0.000	-0.066
MKT, SMB, VAL, REV, NET	2.957	0.000	0.031	0.208	-0.574	0.000	-0.092
MKT, SMB, VAL, MOM, REV, NET	2.784	0.000	0.030	0.216	-0.622	0.000	-0.126

Selecting Crypto Factors —— A Horse Race of Factor Models

- Fama and French (2018): LHS and RHS approaches.

- **RHS approach**

- Method 1. Factor spanning regression: regress one factor on the other four factors

	MKT	SMB	MOM	VAL	NET
Intercept	0.014	0.051	0.038	0.036	0.030
	(2.039)**	(4.284)***	(3.380)***	(5.502)***	(1.820)*
MKT		0.037	0.081	-0.035	0.112
		(0.470)	(0.620)	(-0.409)	(1.011)
SMB	0.015		-0.043	0.064	0.044
	(0.509)		(-1.019)	(1.109)	(0.716)
MOM	0.031	-0.040		-0.047	0.066
	(0.625)	(-1.163)		(-1.238)	(0.807)
VAL	-0.027	0.122	-0.098		0.054
	(-0.395)	(1.214)	(-1.420)		(0.443)
NET	0.033	0.031	0.051	0.020	
	(0.998)	(0.695)	(0.783)	(0.424)	
Adjusted R square	-0.004	0.021	0.005	0.013	-0.004

Selecting Crypto Factors —— A Horse Race of Factor Models

- Fama and French (2018): LHS and RHS approaches.
- **RHS approach**

- Method 2. Max Squared Sharpe Ratio Test (Barillas and Shanken, 2016)

Define f as a model's factors, $\bar{r}$ as the vector of sample mean excess return, $\hat{V}$ as the variance-covariance matrix of assets, The squared Sharpe ratio is: $Sh^2(f) = \bar{r}'\hat{V}^{-1}\bar{r}$.

	$Sh^2(f)$	Marginal Contributions to $Sh^2(f)$					
		MKT	SMB	MOM	REV	VAL	NET
MKT_LTW, SMB_LTW, MOM_LTW	0.0327	1.46%	0.05%	1.32%			
MKT, SMB, MOM	0.1295	1.34%	8.25%	3.23%			
MKT, SMB, REV	0.1355	1.81%	9.46%		3.83%		
MKT, SMB, VAL	0.1807	1.89%	6.69%			8.35%	
MKT, SMB, NET	0.1217	1.36%	7.55%				2.45%
MKT, SMB, VAL, MOM	0.2215	1.58%	6.99%	4.08%		9.20%	
MKT, SMB, VAL, REV	0.2071	2.05%	7.91%		2.64%	7.16%	
MKT, SMB, VAL, NET	0.2028	1.62%	6.40%			8.11%	2.21%
MKT, SMB, VAL, MOM, NET	0.2402	1.37%	6.69%	3.74%		8.93%	1.87%
MKT, SMB, VAL, MOM, REV	0.2530	1.73%	8.38%	4.59%	3.15%	7.91%	
MKT, SMB, VAL, REV, NET	0.2300	1.77%	7.61%		2.72%	6.92%	2.28%
MKT, SMB, VAL, MOM, REV, NET	0.2723	1.51%	8.08%	4.23%	3.21%	7.65%	1.93%

Token Classification

- No consensus has been reached on the proper classification of tokens.
- Classification based on how cryptocurrencies derive value and function economically.
- Cong and Xiao (2021): general payment, platform token, product token, and security token.
- Manually classify the 616 cryptocurrencies in the Core Sample.

	Number	Start date	Mean	Skewness	Kurtosis	Volume	Volatility	Total addresses	Total addresses with balances	Active addresses
General	28	2014/1/1	5,362,838,000	2.590	9.632	499,788,000	0.033	33,538,650	2,004,398	78,094
Platform	483	2016/5/11	138,725,100	3.616	15.438	31,412,470	0.060	1,183,589	105,168	11,407
Product	72	2017/6/7	40,319,800	3.052	12.981	4,537,450	0.078	33,055	19,392	138
Security	26	2016/12/28	33,073,930	1.634	4.602	2,825,987	0.096	24,514	16,113	101
Total	605									

Classification and Segmentation

- Market segmentation in the cryptocurrency market
  - ✓ For each category, split cryptocurrencies into quintiles according to their characteristics.
  - ✓ The long-short (5-1) spread portfolios in all categories generate negative returns across size quintiles and positive returns in value quintiles.
  - ✓ Platform Tokens generate significantly larger network spread returns, which is consistent with the notion that the network effect is important to the Platform Token (Cong, Li, and Wang, 2021a, and Cong and Xiao, 2021).

Panel D: BAgrowth												
	Low	2	3	4	**High**	H-L	**Low**	2	3	4	**High**	H-L
	Mean						*t*-statistic (Mean)					
General	0.016	0.015	0.045	0.009	0.036	0.020	1.269	1.464	2.320	1.294	2.014	1.124
Platfor m	0.017	0.017	0.023	0.029	0.036	0.019	1.181	1.318	1.730	2.004	2.210	1.964
Product	0.034	-0.001	0.030	0.023	0.012	-0.022	1.140	-0.075	1.578	1.586	0.864	-0.848
Security	0.055	0.005	0.063	0.019	0.029	-0.026	2.370	0.227	2.246	1.327	1.173	-0.990

Classification and Segmentation

- Market segmentation in the cryptocurrency market
  - ✓ Following Hou, Karolyi and Kho (2011), compare relative performance of global, local, and international versions of C-CAPM, LTW-3, and C-5.
- Test assets: 16 sets of characteristic-sorted decile portfolios as test assets (4 characteristics × 4 categories) to compare the performance of different models.
  - ✓ size, value, momentum, and network characteristics

	Global factor model						Local factor model						International factor model					
	GRS	pGRS	$A\|a\|$	AR^2	R_C^2	$p(R_C)$	GRS	pGRS	$A\|a\|$	AR^2	R_C^2	$p(R_C)$	GRS	pGRS	$A\|a\|$	AR^2	R_C^2	$p(R_C)$
Total																		
C-CAPM	1.307	4	0.031	0.128	0.063	10	1.175	3	0.013	0.198	0.038	8	1.336	3	0.015	0.295	0.116	8
LTW 3-factor	1.579	5	0.025	0.247	-0.499	8	1.244	3	0.017	0.276	0.472	13	1.509	5	0.019	0.366	0.365	13
C-5	1.614	5	0.025	0.256	-0.487	8	1.185	3	0.017	0.326	0.548	13	1.549	6	0.021	0.425	0.468	12

- ✓ Total for p(GRS) indicates how many tests fail;
- ✓ Total for GRS, average absolute alpha ($A|a|$), average adjusted R square (AR^2), and constrained R square (R_C^2) denote the average value;
- ✓ Total for p(R_C^2) indicates how many tests have positive constrained R square with p-value <=0.05, i.e., p value is positive at the 5% level.
- ✓ For total p(R_C^2), a greater value indicates better performance; it is the opposite for total p(GRS).

Key Takeaways

- Crypto value and network adoption premia; reversal for small tokens and momentum for big tokens.
- A five-factor model (C-5) with crypto value, network, market, size, and momentum best explains the cross section of crypto asset returns.
- First systematic categorization of about 700 cryptocurrencies based on their economic functionality.
- Documentation of strong market segmentation across different categories.