Should You Listen to Crypto YouTubers?

37^{th} Workshop, Austrian Working Group on Banking and Finance

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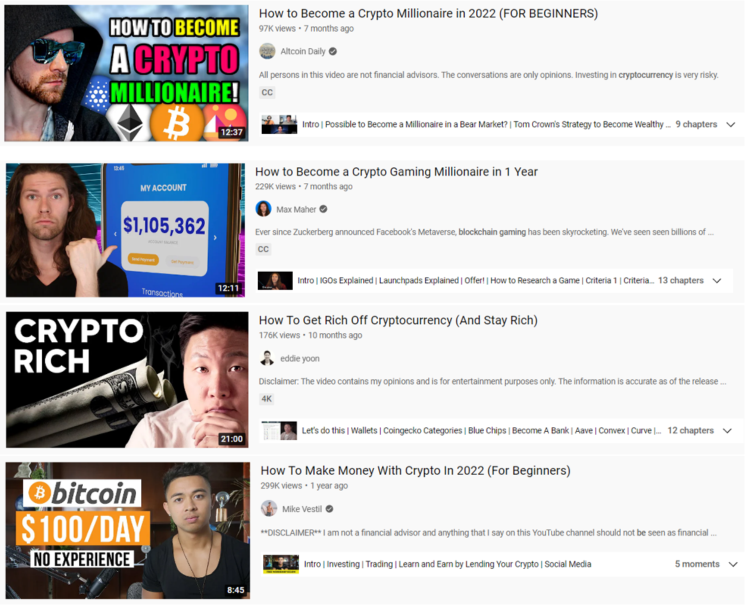
Let's get rich ... ?



Motivation

- Crypto-influencers → state to know about lucrative projects, coins, tokens ...
- *'Gems'*: relatively unknown, low market capitalization, massive potential
- Often state to buy/invest in the mentioned project too → promotion reinforcement
- Selling tips rarely if ever given
- 20,000 and 13,000 distinct cryptocurrencies on coingecko.com and coinmarketcap.com *(as of July 2022)*, huge number of small/tiny crypto projects (by MC = market capitalization), also *'scam tokens'* and *'shitcoins'* are listed ...
- Some videos end with explicit *shopping list*, buying tips, top 5 ...

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Hypothesis

Reactions on price and trading volume can be observed after YouTubers promote crypto-coins with a small market capitalization in their videos.

Literature & Research Questions

Related works on the topic *'Social Media and Cryptos'*

- Shen et al. [2019]: 'Does Twitter predict Bitcoin?'
- Naeem et al. [2021]: 'Does Twitter happiness sentiment predict cryptocurrency?'
- Aslanidis et al. [2021]: 'The link between Bitcoin and Google Trends attention'
- Aslanidis et al. [2022]: 'The link between cryptocurrencies and Google Trends attention'
- Vakilinia [2022]: 'cryptocurrency giveaway scam with YouTube live stream'
- Prasad et al. [2022]: 'Sentiment Analysis on cryptocurrency using YouTube comments'

Research questions

What effect can be observed, after popular crypto-influencers release YouTube-videos in which they mention tokens/coins with a small market capitalization

a) on the tokens/coins price
b) on the trading volume?
c) Does the market capitalization (MC) of the mentioned tokens/coins matters?

Data

– Observation period: 08/24/2021 - 02/28/2022

Channel name	# subscribers	# events
Bitboy Crypto	1.45m	17
Alex Becker's Channel	1.30m	35
Max Maher	896,000	7
CryptoBanter	577,000	156
Lark Davis	487,000	7
Altcoin Buzz	374,000	28
Crypto Love	243,000	55

(as of 07/26/2022)

– YouTube channel criteria: 1. sufficient subscriber (more than 200,000)
2. occasionally covering lower cap coins and token
– Event = any time one of the YouTube channels listed above mentions a low-cap coin or token in one of their videos
– Low-cap: coins/tokens with a MC <USD 100m at the time of the video release
– 305 events in total, median MC USD 28m
– Data on MC, price and trading volume from Coingecko.com and Coinmarketcap.com
– Data on Royalton Crix Index from royalton-crix.com → proxy for the crypto market

Methodology I

- Standard event study, video release day = event day, $t =$
- Event window: 11-days, centered around the release-date, $\{-5; -4; \ldots; +5\}$
- Estimation window: 40 days prior to the event window, $\{-45; -44; \ldots; -6\}$
- Price reactions: measured by daily log-returns, $r_t = \ln(P_t / P_{t-1})$,
- Trading behavior: daily dollar trading volume, normalized by its mean (due to highly heterogeneity in terms of levels)

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1. Returns estimation window time series of token i:

Market model:

$$r_{it} = \ _i + \ _i \ r_{mt} + \ _{it} \tag{1}$$

,	→	Regression coefficients
r_{mt}	→	Market returns derived from CRIX data
	→	Error term

– Abnormal returns (AR):

$$AR_{it} = r_{it} \quad \hat{}_i \quad \hat{}_i \ r_{mt} \tag{2}$$

$\hat{}_i$, $\hat{}_i$	→	Regression coefficient estimators

Methodology II

- Average abnormal returns (AAR):

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \qquad (3)$$

$N \quad \rightarrow \quad$ Number of events (305)

- Standard deviation of AAR:

$$[AAR] = \left[\frac{1}{39} \sum_{t=\quad 45}^{6} (AAR_t \quad \overline{AAR})^2 \right]^{1=2} \qquad (4)$$

$\overline{AAR} \quad \rightarrow \quad$ arithmetic mean of AAR in the estimation window

- t-test for AAR in the event window:

$$t = \frac{AAR_t}{[AAR]} \qquad (5)$$

Methodology III

2. Trading volume:

– Abnormal trading volume:

$$AV_i = V_i \quad \bar{V}_i \tag{6}$$

$\bar{V}_i \quad \rightarrow \quad$ average trading volume in the estimation window

– Sign test (CorradoZivney, 1992):

$$G_{it} = sign(AV_{it} \quad median(AV_i)) \tag{7}$$

– test statistic with trading volume abnormal from zero asymptotically follows a normal distribution:

$$t_{G;t} = \frac{1}{\sqrt{N}} \sum_{N} \frac{G_{it}}{[G]} \tag{8}$$

$$[G] = \sqrt{\frac{1}{51} \sum_{t=\ 45}^{5} \left(\frac{1}{\sqrt{N}} \sum_{N} G_{it} \right)^2} \tag{9}$$

$N \quad \rightarrow \quad$ Number of events (304)

Results I - Price reaction

	total (n = 305)	
t	**AAR (in %)**	**CAAR (in %)**
-5	1.759* (1.901)	1.759* (1.901)
-4	0.829 (0.896)	2.588* (1.978)
-3	-0.9 (-0.973)	1.688 (1.053)
-2	0.427 (0.462)	2.115 (1.143)
-1	1.092 (1.18)	3.207 (1.55)
0	**0.49 (0.53)**	**3.697 (1.631)**
1	**6.729***** (7.274)	**10.426***** (4.259)
2	-0.354 (-0.382)	10.073*** (3.849)
3	-2.896*** (-3.13)	7.177*** (2.586)
4	-1.397 (-1.51)	5.779* (1.975)
5	-1.011 (-1.093)	4.769 (1.554)

Price reaction for the total sample (N = 305). Event day set as day t = 0. AAR = average abnormal returns, CAAR = cumulative average abnormal returns. Returns as percentages, ***,** and * denote significance at 1, 5 and 10 percent level, t-values in parenthesis.

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Results II - Price reaction in subsamples by MC

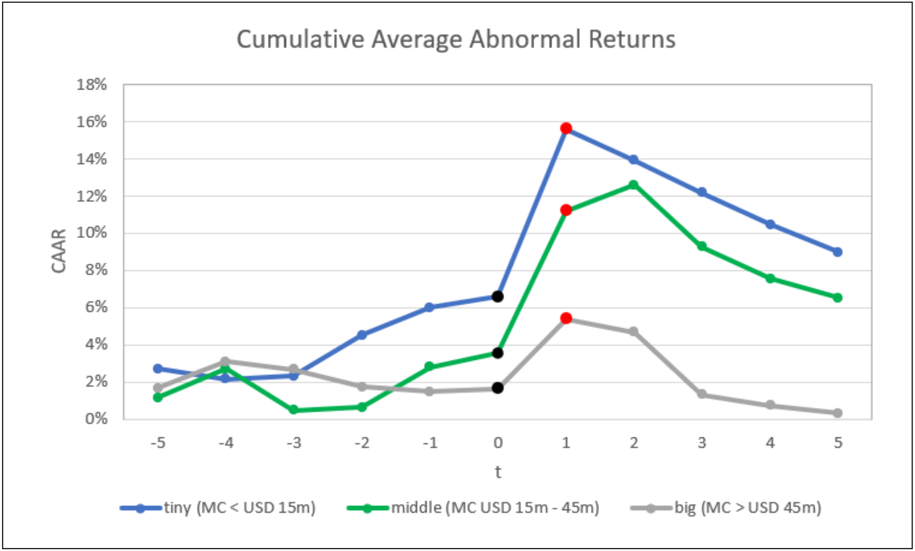
	MC < USD 15m (n = 96)		MC USD 15m - 45m (n = 109)		MC > USD 45m (n = 100)	
t	AAR (in %)	CAAR (in %)	AAR (in %)	CAAR (in %)	AAR (in %)	CAAR (in %)
-5						
-4						
-3						
-2						
-1						
0						
1						
2						
3						
4						
5						

Results II - Price reaction in subsamples by MC

	MC <USD 15m (n = 96)		MC USD 15m - 45m (n = 109)		MC >USD 45m (n = 100)	
t	**AAR (in %)**	**CAAR (in %)**	**AAR (in %)**	**CAAR (in %)**	**AAR (in %)**	**CAAR (in %)**
-5	2.707** (2.041)	2.707** (2.041)	1.137 (0.852)	1.137 (0.857)	1.682 (1.338)	1.682 (1.268)
-4	-0.562 (-0.424)	2.145 (1.143)	1.557 (1.167)	2.694 (1.436)	1.396 (1.11)	3.078 (1.641)
-3	0.166 (0.125)	2.311 (1.006)	-2.229 (-1.671)	0.465 (0.202)	-0.403 (-0.321)	2.675 (1.164)
-2	2.195 (1.654)	4.506* -1.698	0.177 (0.133)	0.642 (0.242)	-0.940 (-0.748)	1.735 (0.654)
-1	1.511 (1.139)	6.017** (2.028)	2.164 (1.622)	2.806 (0.946)	-0.274 (-0.218)	1.461 (0.492)
0	**0.582** **(0.439)**	**6.598**** **(2.031)**	**0.751** **(0.563)**	**3.557** **(1.095)**	**0.190** **(0.151)**	**1.651** **(0.508)**
1	**9.014***** (6.795)	**15.613***** (4.448)	**7.653***** (5.737)	**11.211***** (3.194)	**3.751***** (2.983)	**5.402** (1.539)
2	-1.686 (-1.271)	13.927*** (3.711)	1.379 (1.033)	12.589*** (3.355)	-0.737 (-0.586)	4.665 (1.243)
3	-1.743 (-1.314)	12.184*** (3.061)	-3.315** (-2.485)	9.274** (2.33)	-3.364** (-2.676)	1.301 (0.327)
4	-1.724 (-1.299)	10.46** (2.493)	-1.716 (-1.287)	7.558* (1.802)	-0.565 (-0.449)	0.736 (0.175)
5	-1.491 (-1.124)	8.969** (2.038)	-1.042 (-0.781)	6.516 (1.481)	-0.426 (-0.339)	0.310 (0.07)

Price reaction for the subsamples (by market capitalization). Event day set as day $t = 0$. AAR = average abnormal returns, CAAR = cumulative average abnormal returns. Returns as percentages, ***,** and * denote significance at 1, 5 and 10 percent level, t-values in parenthesis.

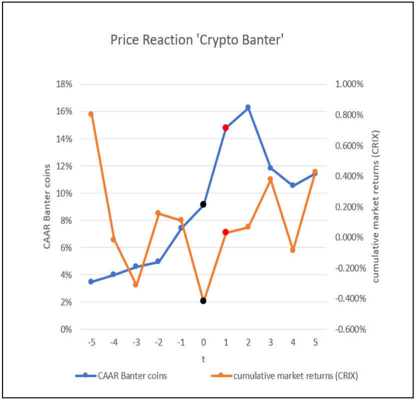
Results II - Price reaction in subsamples by MC



Results III - Price reaction in subsample 'Crypto Banter'

t	Crypto Banter (n = 156) AAR (in %)	CAAR (in %)
-5	3.477** (2.683)	3.477** (2.683)
-4	0.515 (0.397)	3.992** (2.178)
-3	0.610 (0.471)	4.603** (2.05)
-2	0.366 (0.282)	4.968* (1.917)
-1	2.424* (1.87)	7.392** (2.551)
0	**1.748 (1.349)**	**9.141*** (2.879)**
1	**5.644***** (4.355)	**14.785***** (4.312)
2	1.478 (1.14)	16.263*** (4.436)
3	-4.426*** (-3.415)	11.837*** (3.044)
4	-1.303 (-1.005)	10.534** (2.57)
5	0.890 (0.686)	11.424** (2.657)

Price reaction for the subsample 'events by crypto banter'. Event day set as day t = 0, AAR = average abnormal returns, CAAR = cumulative average abnormal returns. Returns as percentages, ***,** and * denote significance at the 1, 5 and 10 percent level, t-values in parenthesis.



Results IV - Volume reaction

	total (n = 304)				
t	**AAV**				
-5	0.230 (0.459)				
-4	0.301 (0.885)				
-3	0.341 (0.951)				
-2	0.299 (0.557)				
-1	0.296 (0.852)				
0	**0.323*** **(1.508)**				
1	1.008*** (3.933)				
2	0.726*** (2.655)				
3	0.358 (1.082)				
4	0.326* (1.377)				
5	0.412* (1.377)				

Volume Reaction - total sample, subgroups by MC and subgroup 'Crypto Banter'. Event day set as t = 0. Results denoted as average abnormal volume, ***,** and * denote significance at 1, 5 and 10 percent level, z-values in parenthesis.

Results IV - Volume reaction

	total (n = 304)	MC < USD 15m (n = 95)	MC USD 15m - 45m (n = 109)	MC > USD 45m (n = 100)	
t	**AAV**	**AAV**	**AAV**	**AAV**	
-5	0.230 (0.459)	0.206 (0)	0.237 (0.424)	0.245 (1.107)	
-4	0.301 (0.885)	0.257 (1.022)	0.225 (0.742)	0.427 (1.217)	
-3	0.341 (0.951)	0.424** (1.93)	0.055 (0)	0.574* (1.328)	
-2	0.299 (0.557)	0.477 (1.136)	0.121 (0)	0.324 (0.775)	
-1	0.296 (0.852)	0.213 (1.022)	0.404 (0.954)	0.259 (0.885)	
0	**0.323*** **(1.508)**	**0.408*** **(1.59)**	**0.352**** **(1.908)**	**0.212*** **(1.55)**	
1	1.008*** (3.933)	1.595*** (3.293)	0.912*** (6.361)	0.556*** (3.431)	
2	0.726*** (2.655)	0.901** (2.158)	0.846*** (4.559)	0.429** (2.103)	
3	0.358 (1.082)	0.321 (0.454)	0.448** (1.696)	0.295* (1.439)	
4	0.326* (1.377)	0.139 (0.114)	0.582*** (2.544)	0.223** (1.882)	
5	0.412* (1.377)	0.190 (0.454)	0.741** (2.226)	0.266** (1.882)	

Volume Reaction - total sample, subgroups by MC and subgroup 'Crypto Banter'. Event day set as $t = 0$. Results denoted as average abnormal volume, ***,** and * denote significance at 1, 5 and 10 percent level, z-values in parenthesis.

Results IV - Volume reaction

	total (n = 304)	MC < USD 15m (n = 95)	MC USD 15m - 45m (n = 109)	MC > USD 45m (n = 100)	Crypto Banter (n = 156)
t	**AAV**	**AAV**	**AAV**	**AAV**	**AAV**
-5	0.230 (0.459)	0.206 (0)	0.237 (0.424)	0.245 (1.107)	0.160 (-0.605)
-4	0.301 (0.885)	0.257 (1.022)	0.225 (0.742)	0.427 (1.217)	0.091 (-0.908)
-3	0.341 (0.951)	0.424** (1.93)	0.055 (0)	0.574* (1.328)	0.161 (-0.605)
-2	0.299 (0.557)	0.477 (1.136)	0.121 (0)	0.324 (0.775)	0.078 (-0.968)
-1	0.296 (0.852)	0.213 (1.022)	0.404 (0.954)	0.259 (0.885)	0.257 (-0.847)
0	**0.323*** **(1.508)**	**0.408*** **(1.59)**	**0.352**** **(1.908)**	**0.212*** **(1.55)**	**0.262** **(0.968)**
1	1.008*** (3.933)	1.595*** (3.293)	0.912*** (6.361)	0.556*** (3.431)	0.769*** (3.874)
2	0.726*** (2.655)	0.901** (2.158)	0.846*** (4.559)	0.429** (2.103)	0.628*** (2.421)
3	0.358 (1.082)	0.321 (0.454)	0.448** (1.696)	0.295* (1.439)	0.292 (1.211)
4	0.326* (1.377)	0.139 (0.114)	0.582*** (2.544)	0.223** (1.882)	0.384 (1.029)
5	0.412* (1.377)	0.190 (0.454)	0.741** (2.226)	0.266** (1.882)	0.255 (0.061)

Volume Reaction - total sample, subgroups by MC and subgroup 'Crypto Banter'. Event day set as t = 0. Results denoted as average abnormal volume, ***,** and * denote significance at 1, 5 and 10 percent level, z-values in parenthesis.

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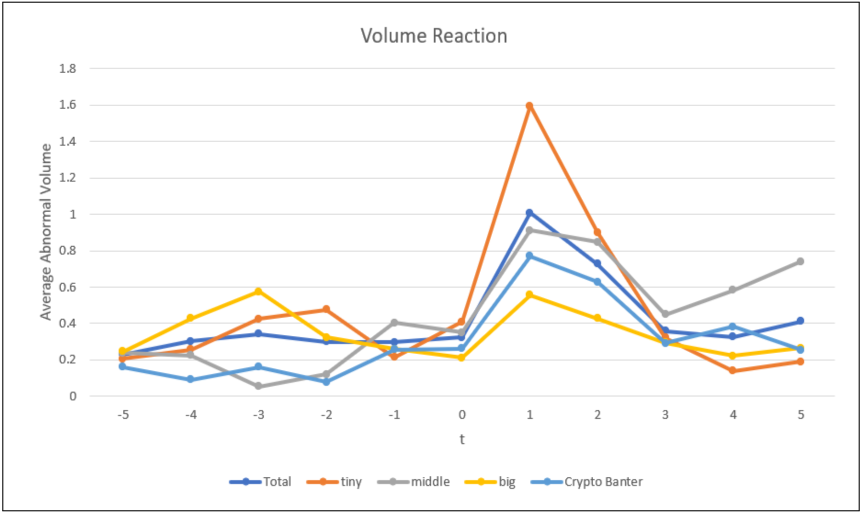

Conclusion

YouTubers have a kind of (short-lived) price impact on small-cap coins (MC <USD 100m)

The smaller the MC, the larger the effect

Similar results for trading volume (peak 1 day after the event, largest effect for tiny coins)

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References I

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