Discussion of: Are Cryptos Different? Evidence from Retail Trading Shimon Kogan, Igor Makarov, Marina Niessner, and Antoinette Schoar

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Discussion Outline

- Review of Results
- Optimal Portfolio Construction
- Value, Momentum and Reversal in Common Stocks
 - Calibration
- Why are cyptocurrencies different?

- Motivating Question: How do retail investors trade cryptocurrencies?
 - How is this different that they way they trade other asset classes?
- **Key Finding**: Retail traders of cryptocurrencies follow a positive-feedabck (or "hodling") strategy
 - Contrasts with a contrarian strategy in stocks and in gold.
- Why?: KMNS aruge that this is because these retail traders use a different perceived RGP for crypto than for other asset classes.
 - Specifically, they believe that high returns will lead to a higher likelihood of broad adoption of the cryptocurrency.
- Why do we care?:
 - Understanding prices requires understanding demand (Koijen and Yogo, 2019).
 - We need to understand how and why demand for an asset changes with its characteristics.

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Share-change regressions:

Table 3A, Crypocurrencies:

	Log(total share change)			Log(active share change)			
	All (1)	$\stackrel{ m Ret>0}{ m (2)}$	$\frac{\text{Ret} \leq 0}{(3)}$	All (4)	$\stackrel{ m Ret>0}{ m (5)}$	$\frac{\text{Ret} \leq 0}{(6)}$	
Log(Ret)(z)	0.035***	0.039***	0.031***	-0.001	0.002	-0.006***	
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Log(CR past 1 week) (z)	0.002^{**}	0.005^{**}	-0.000	0.003^{**}	0.004^{**}	0.001	
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	
Log(CR past 1 month) (z)	0.001	0.002	-0.001	0.000	0.001	0.000	
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	
Log(CR past 3 months) (z)	-0.004**	<mark>-0.003</mark>	-0.006**	-0.005***	-0.003^{*}	-0.007^{**}	
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	
Log(CR past 6 months) (z)	0.005^{**}	0.002	0.007^{**}	0.004^{**}	0.000	0.008^{**}	
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	
Log(Ret Wealth)(z)				0.001	-0.000	0.004^{**}	
				(0.001)	(0.002)	(0.002)	
Log(Ret Net Inflows)(z)				0.006^{***}	0.006^{***}	0.004^{**}	
				(0.001)	(0.002)	(0.002)	
D9	0.225	0.278	0.971	0.022	0.029	0.025	
R2	0.325	0.378	0.271	0.023	0.032	0.035	
Observations	3,586	1,866	1,720	3,586	1,866	1,720	

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Share-change regressions:

Table 3B, Common stocks:

	Log(<mark>total</mark> share change)			Log(<mark>active</mark> share change)		
	All (1)	$\stackrel{ m Ret>0}{ m (2)}$	$\frac{\text{Ret} \leq 0}{(3)}$	All (4)	$\stackrel{ m Ret>0}{ m (5)}$	$\frac{\text{Ret} \leq 0}{(6)}$
Log(Ret) (z)	-0.006***	-0.006**	-0.006**	-0.026***	-0.024^{***}	-0.028***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(CR past 1 week) (z)	<mark>-0.003**</mark>	<mark>-0.005**</mark>	-0.001	-0.003**	-0.005^{***}	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 1 month) (z)	-0.002	-0.003*	-0.001	-0.002^{*}	-0.004^{**}	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 3 months) (z)	0.002	0.004	-0.001	0.002	0.004	-0.001
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Log(CR past 6 months) (z)	0.001	-0.000	0.002	0.002	0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(Ret Wealth)(z)				0.006^{***}	0.004^{**}	0.007^{**}
				(0.002)	(0.002)	(0.003)
Log(Ret Net Inflows)(z)				-0.000	0.000	-0.001
				(0.001)	(0.001)	(0.002)
Da	0.001	0.001	0.001	0.000	0.000	0.011
R2	0.001	0.001	0.001	0.008	0.006	0.011
Observations	170,878	87,894	82,984	170,878	87,894	82,984

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Share-change regressions:

Table 7A, Active Investors:

	Log(<mark>active</mark> share change)						
		Cryptos		Top 200 Stocks			
	All	$\operatorname{Ret}>0$	Ret≤0	All	$\operatorname{Ret}>0$	$\operatorname{Ret} \leq 0$	
	(1)	(2)	(3)	(4)	(5)	(6)	
Log(Ret)(z)	-0.002	-0.001	-0.002	-0.044^{***}	-0.058^{***}	-0.047^{**}	
	(0.001)	(0.009)	(0.008)	(0.003)	(0.005)	(0.005)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
R2	0.127	0.135	0.126	0.010	0.008	0.009	
Observations	3,586	1,866	1,720	167,305	86,002	81,303	

Table 7B, Non-Active Investors:

	Log(<mark>active</mark> share change)						
		Cryptos		Top 200 Stocks			
	All (1)	$\stackrel{ m Ret>0}{ m (2)}$	$\operatorname{Ret} \leq 0$ (3)	All (4)	$\stackrel{ m Ret>0}{ m (5)}$	$\operatorname{Ret} \leq 0$ (6)	
Log(Ret) (z)	-0.002 (0.009)	0.023 (0.019)	-0.013^{*} (0.007)	<mark>-0.005</mark> (0.005)	<mark>-0.016*</mark> (0.009)	0.000 (0.008)	
Controls R2 Observations	Yes 0.020 3,542	Yes 0.029 1,845	Yes 0.024 1,697	Yes 0.004 131,419	Yes 0.004 67,758	Yes 0.004 63,661	

Stock and cryptocurrency return patterns

Similar to stocks, cryptocurrencies do not display meaningful autocorrelation at the daily level. ... During our period, a standard deviation increase in day t's returns is associated with a -0.2% change in day t+1's returns. This result is not statistically significant even at a 10% level. (p.3, & fn. 4)

- This isn't a test with high statistical power (see e.g., Daniel, 2001)
- What do more powerful tests reveal about autocorrelations in stocks and crypto?
 See also Liu and Tsyvinski (2021) and Liu, Tsyvinski, and Wu (2022)

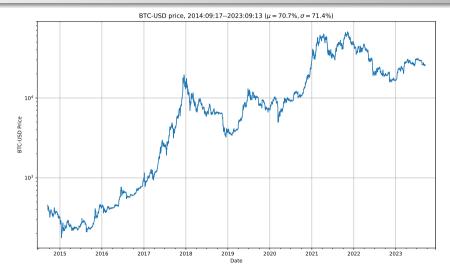
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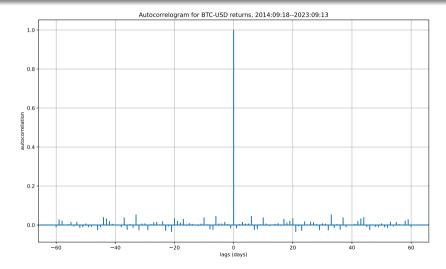
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BTC Returns Stock Returns

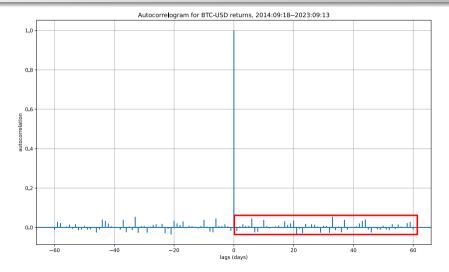
BTC Prices, 2014–2023



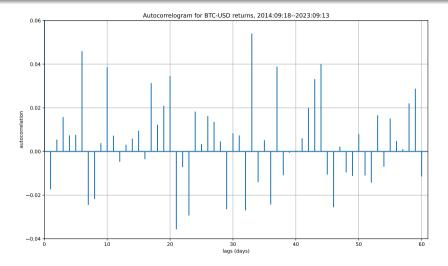
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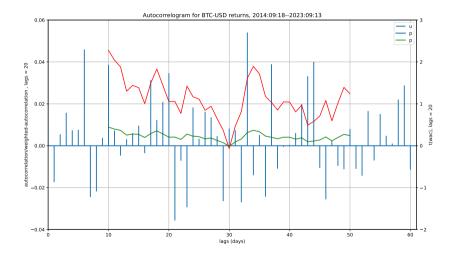
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Stock Return Autocorrelations

At horizons ...

- ... of ≤ 1 day, there is some positive autocorrelation (intraday momentum)
 - Bogousslavsky (2016)
- ... from 2 days–1 month, residual returns are negatively autocorrelated on non-information release dates (short-horizon reversal)
 - Jegadeesh (1990); Lehmann (1990); Tetlock (2011); Nagel (2012); Collin-Dufresne and Daniel (2015)
- ... from 1 month–1 year, there is positive autocorrelation (momentum)
 - Jegadeesh and Titman (1993)
- ... from 2–5 years, there is negative autocorrelation (long-horizon reversal)
 - DeBondt and Thaler (1985, 1987); Daniel and Titman (2006)

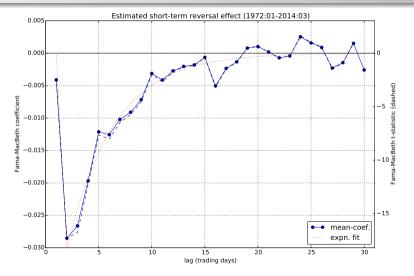
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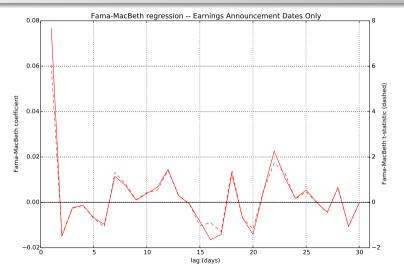
BTC Returns Stock Returns

Stock Return Autocorrelations



BTC Returns Stock Returns

Stock Return Autocorrelations



How much trade should you see? – A Rough Calibration

Setup:

- Assume excess return $\mathbb{E}[r_m]$ of 5%/year (0.02%/day).
- Mkt annualized volatility is 10% (=0.63% daily vol)
 - Annualized $SR_m = 0.5$, daily $SR_m = 0.0316$

Suppose $\rho = 0.01$ autocorrelation, and a -1σ move.

- \Rightarrow new $\mathbb{E}[r] \approx 0.02 0.0063 = 0.0137$
- $\bullet\,$ This suggests that you should trade out of 31.4% of your position.
- For a $+1\sigma$ move of 0.63%, you should should increase your position by 31.4%.

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- For a $+1\sigma$ move of 0.63%, you should should increase your position by 31.4%.

Why so little trading?

- Investors are clearly trading a lot less than this.
- Perhaps the problem is that the (effective) transaction costs they are paying are certainly not zero.
 - Trading costs are likely higher than eToro's stated costs.
 - quadratic costs won't matter for these small investors, but fixed/linear will.
- An interesting question would be whether the active stock investors actually make money on their trades.

The Model of Crypto returns

We conjecture that retail investors have a model of cryptocurrency prices, where positive returns increase the likelihood of future widespread adoption, which in turn drives up asset prices (and vice versa when prices go down), Investors do not have the same price expectations for other traditional assets where wider adoption has already happened.

- If *all* crypto investors (retail and other) have these beliefs, then, in equilibrium, none of them will buy or sell.
 - However, this would be true *no matter what* their beliefs.
 - This is just an adding-up constraint.
- The model needs a little more structure to this model to make it testable, at least in this way.

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Conclusions & Suggestions

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- The differential patterns in stocks and crypocurrencies are fascinating.
- Understanding the differences, and why they arise important for understand price formation.
- It would be interesting to extend the model and empirical tests to consider magnitudes and different horizons.
- Are the active contrarian investors making money on their trades?
 - Since Barber and Odean (2000), we have been convinced that trading is bad.
 - Is this true for these individual investors?

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