

Sequential Learning, Asset Allocation, and Bitcoin Returns

with James Yae

AFA 2022 Annual Meeting

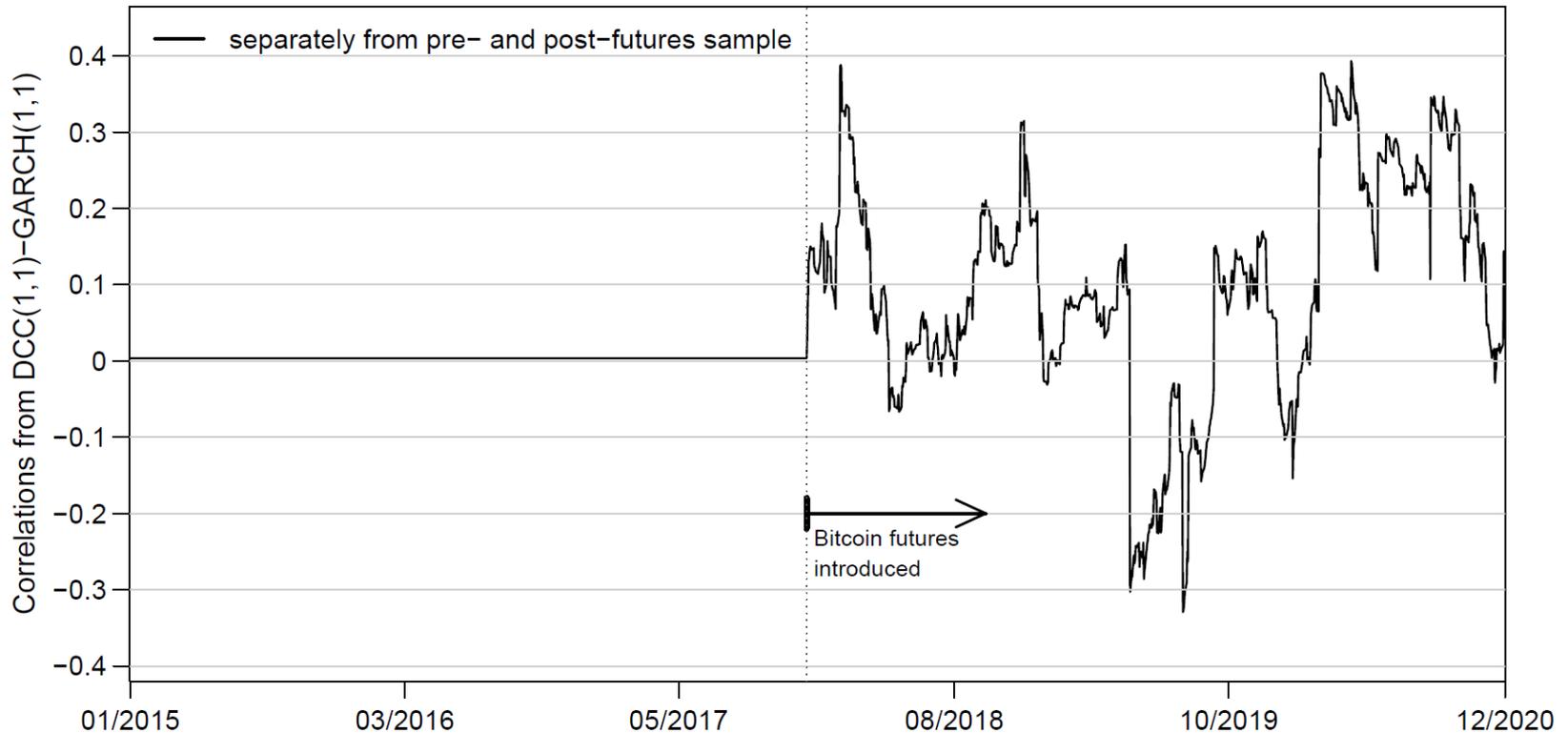
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Structural Break in Correlation

Dynamic Correlation between Bitcoin and S&P500 returns: Pre- and Post-futures



Correlations are time varying only after the inception of Bitcoin futures!



How does it affect investors' behavior who seek portfolio optimization?

Bitcoin Demand Proxy

Optimal weight on Bitcoin (in a BTC-stock market portfolio)

$$w_{b,t} = \frac{\mu_t^* - \rho_t \sigma_t^*}{(\mu_t^* - \rho_t \sigma_t^*) + (\sigma_t^* - \rho_t \mu_t^*) \sigma_t^*} \quad \text{Max Sharpe Ratio!}$$

- Conditional risk premium ratio $\mu_t^* = \mu_{b,t} / \mu_{m,t}$
- Conditional volatility ratio $\sigma_t^* = \sigma_{b,t} / \sigma_{m,t}$

Bitcoin Demand Decomposition

non-speculative + speculative



$$\Delta w_{b,(t-1):t} \triangleq w_{b,t} - w_{b,t-1} = \Delta w_{b,(t-1):t}^{(cor)} + \Delta w_{b,(t-1):t}^{(vol)} + \Delta w_{b,(t-1):t}^{(mean)} + e_t$$

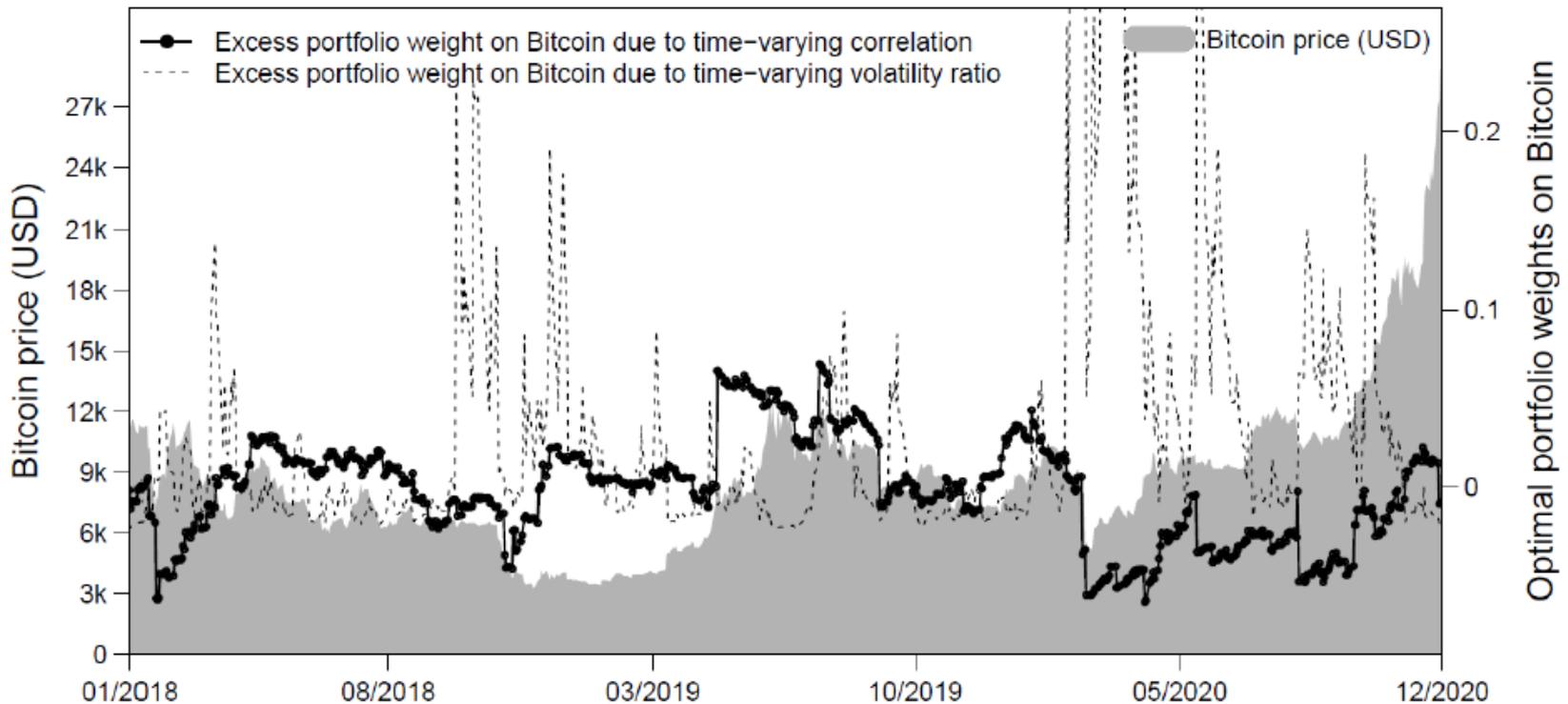
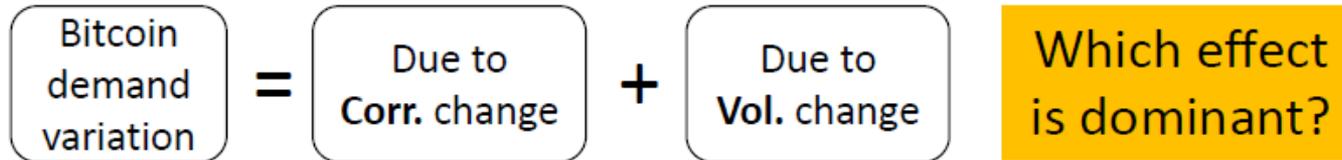
DCC(1,1)-GARCH(1,1) for estimation

$$w_{b,t}^{(mean)} \triangleq w_b(\mu_t^*, \bar{\sigma}^*, \bar{\rho}) \quad \text{investors only learn } \mu_t^*$$

$$w_{b,t}^{(cor)} \triangleq w_b(\bar{\mu}^*, \bar{\sigma}^*, \rho_t) \quad \text{investors only learn } (\rho_t)$$

$$w_{b,t}^{(vol)} \triangleq w_b(\bar{\mu}^*, \sigma_t^*, \bar{\rho}) \quad \text{investors only learn } (\sigma_t^*)$$

Bitcoin Demand Proxy



Daily Bitcoin Return Predictability

$$r_{b,t+1} = b_0 + b_1 \Delta w_{b,(t-1):t}^{(cor)} + b_2 \Delta w_{b,(t-1):t}^{(vol)} + Z_t \gamma + \varepsilon_{t+1}$$

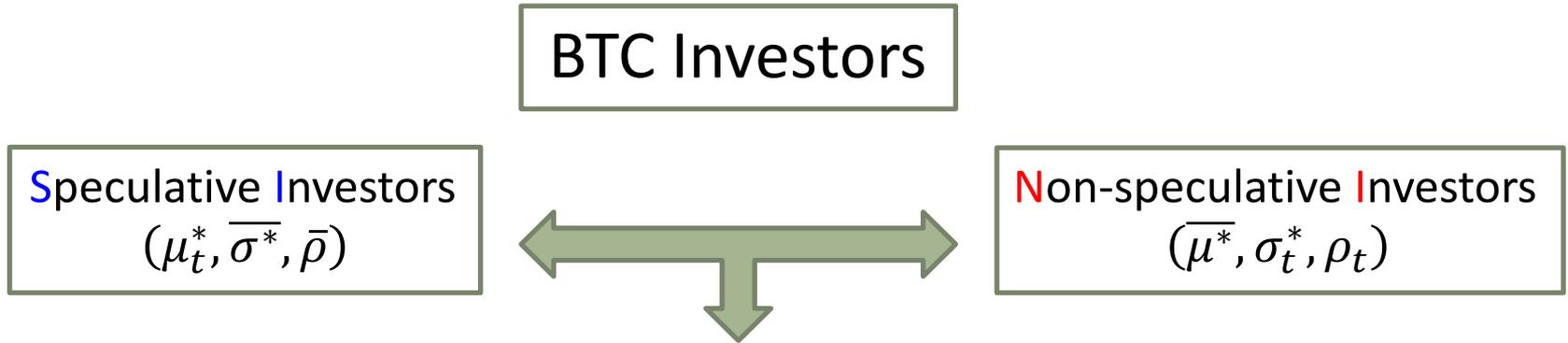
0.5% higher returns with 1 std demand increase

30 times higher est. uncertainty (noisy signal)

Predictor	Post-futures (12/18/2017 to 12/31/2020)					Post-futures before COVID-19 (12/18/2017 to 02/29/2020)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta w_{b,(t-1):t}^{(cor)}$	0.51 (4.15)		0.47 (2.89)	0.47 (2.91)	0.47 (2.80)	0.50 (3.16)		0.48 (2.78)	0.47 (2.63)	0.48 (2.37)
$\Delta w_{b,(t-1):t}^{(vol)}$		0.06 (0.42)	0.03 (0.28)	0.04 (0.30)	0.03 (0.20)		-0.19 (-1.27)	-0.23 (-1.66)	-0.22 (-1.67)	-0.20 (-1.56)
$r_{b,t}$			-0.42 (-1.79)	-0.42 (-1.76)	-0.42 (-1.74)			-0.22 (-0.83)	-0.23 (-0.83)	-0.22 (-0.82)
β_t			0.04 (0.22)	0.06 (0.31)	0.07 (0.31)			0.06 (0.28)	0.07 (0.32)	0.09 (0.40)
$Volume_{b,t}$			-0.58 (-2.59)	-0.55 (-1.35)	-0.55 (-1.39)			-0.74 (-3.52)	-0.91 (-1.93)	-0.87 (-1.78)
$EPU_{b,t}$			0.63 (1.71)	0.64 (1.68)	0.63 (1.76)			0.21 (0.98)	0.20 (0.93)	0.21 (0.96)
Controls			M	MB	MBL			M	MB	MBL
R^2 (%)	1.15	0.01	3.94	3.99	4.00	1.17	0.16	4.04	4.14	4.38
$Adj.R^2$	1.02	-0.12	2.92	2.71	2.47	0.99	-0.02	2.62	2.36	2.24

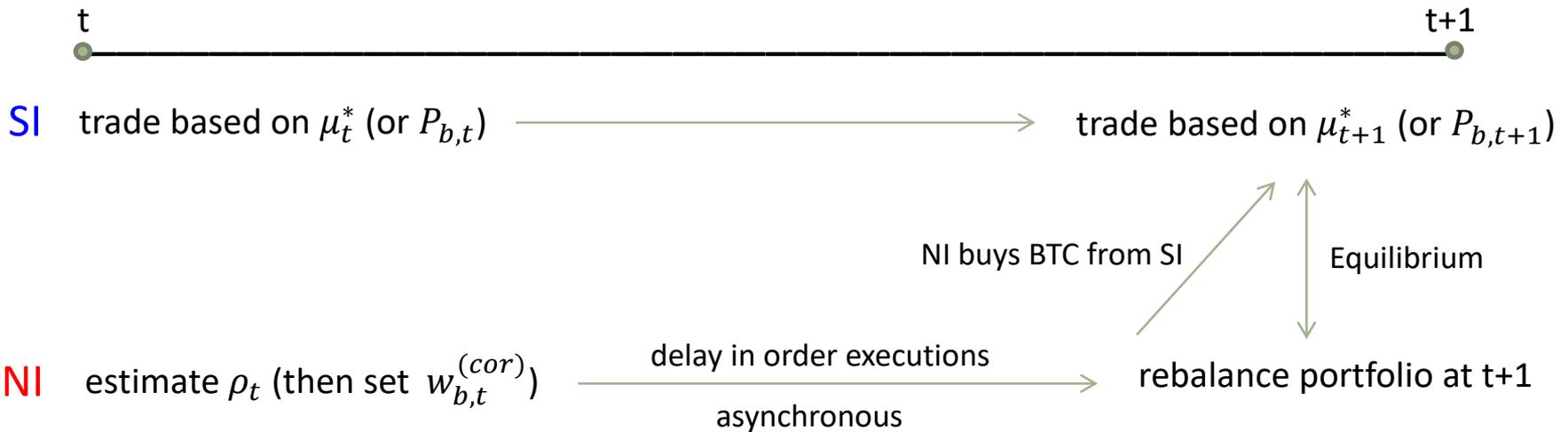
Data are at *daily* frequency. Newey-West t statistics are reported in parenthesis.

Equilibrium Model: Intuition



“asynchronous portfolio rebalancing”

links increase in BTC demand due to ρ_t (or decrease in ρ_t) to higher subsequent BTC returns!



Highlights

1) Bitcoin return predictability:

Increase in daily Bitcoin demand change due to dynamic correlation predicts higher subsequent Bitcoin returns

2) Rational asset allocation:

The empirical pattern is consistent with investors' learning on time-varying correlations and practice on rational portfolio optimization

3) Asynchronous portfolio rebalancing:

We use an equilibrium model to explain how Bitcoin return predictability emerges from asynchronous portfolio rebalancing



The paper also explains:

- Why predictability from $\Delta w_{b,(t-1):t}^{(cor)}$ not $\Delta w_{b,(t-1):t}^{(vol)}$

- Is there out-of-sample predictability?

- other Bitcoin demand proxies?

- Does the evidence show up in other cryptos and other equity markets?

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