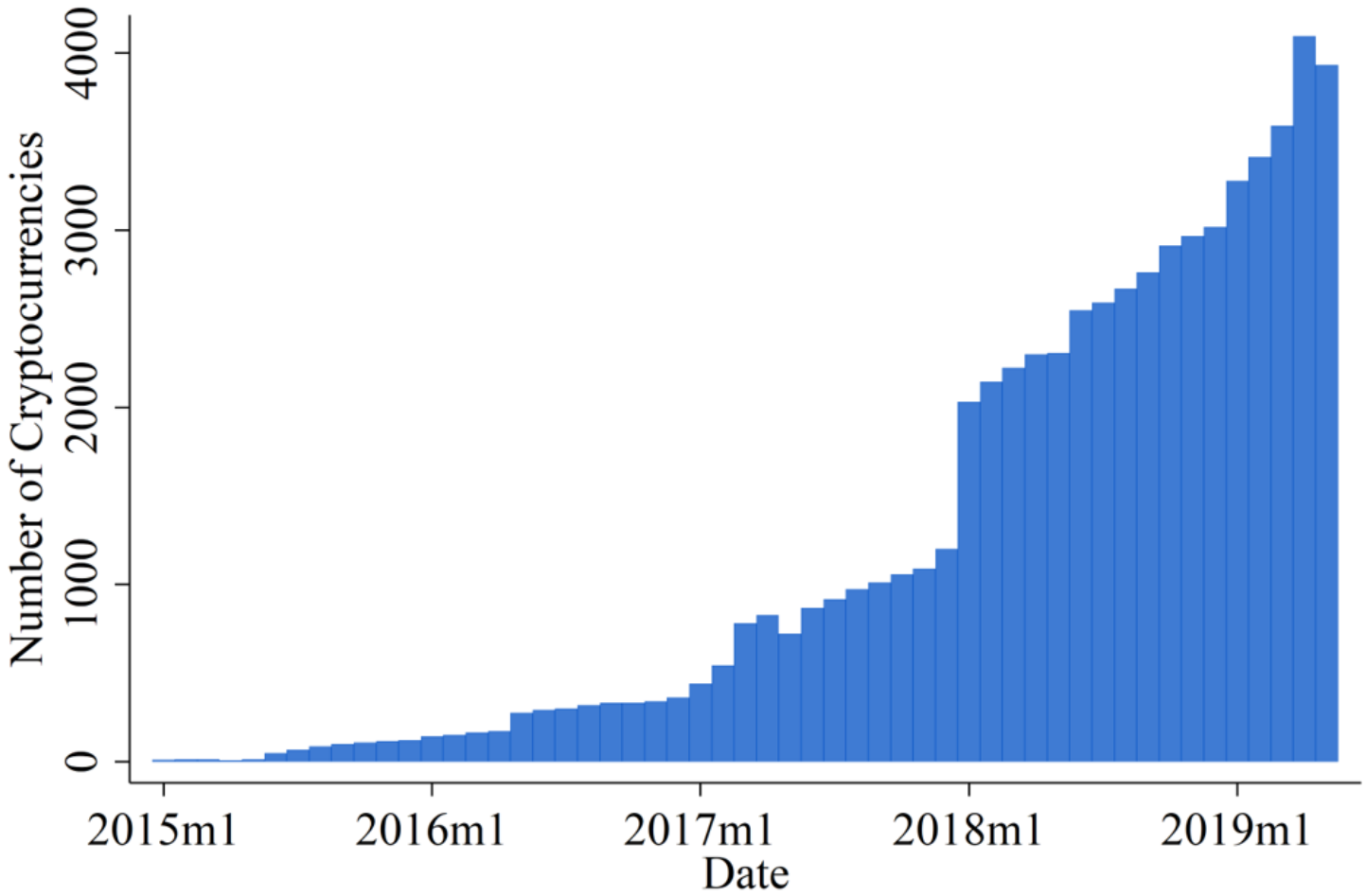
The Structure of Cryptocurrency Returns

Amin Shams
Ohio State University

October 26, 2020

Number of Cryptocurrencies Over Time



What Do We Know about Cryptocurrency Prices?

- What drives cryptocurrency prices?
- What determines the return structure of cryptocurrencies?
- What is the source of the underlying value?
- How do investors think about the value?

What Do We Know about Cryptocurrency Prices?

- What drives cryptocurrency prices?
- What determines the return structure of cryptocurrencies?
- What is the source of the underlying value?
- How do investors think about the value?

What Do We Know about Cryptocurrency Prices?

- What drives cryptocurrency prices?
- What determines the return structure of cryptocurrencies?
- What is the source of the underlying value?
- How do investors think about the value?

What Do We Know about Cryptocurrency Prices?

- What drives cryptocurrency prices?
- What determines the return structure of cryptocurrencies?
- What is the source of the underlying value?
- How do investors think about the value?

Conceptual Framework

Two broad frameworks for pricing assets:

1. Returns can be explained by characteristics such as size, book-to-market, past returns, industry, etc. (e.g. Fama and French (1993) and Daniel and Titman (1997)).
2. Returns can be explained by investor demand. (e.g. Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005))

- Demand for holding cryptocurrencies can be perceived as a sign of adoption, which can affects the value of cryptocurrencies due to the network effect. (e.g. Cong, Li, and Wang (2020) and Sockin and Xiong (2020))

This paper studies the structure and drivers of cryptocurrency returns within the framework of examining crypto investors' demand.

Conceptual Framework

Two broad frameworks for pricing assets:

1. Returns can be explained by characteristics such as size, book-to-market, past returns, industry, etc. (e.g. Fama and French (1993) and Daniel and Titman (1997)).
2. Returns can be explained by investor demand. (e.g. Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005))

- Demand for holding cryptocurrencies can be perceived as a sign of adoption, which can affects the value of cryptocurrencies due to the network effect. (e.g. Cong, Li, and Wang (2020) and Sockin and Xiong (2020))

This paper studies the structure and drivers of cryptocurrency returns within the framework of examining crypto investors' demand.

Conceptual Framework

Two broad frameworks for pricing assets:

1. Returns can be explained by characteristics such as size, book-to-market, past returns, industry, etc. (e.g. Fama and French (1993) and Daniel and Titman (1997)).
2. Returns can be explained by investor demand. (e.g. Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005))

- Demand for holding cryptocurrencies can be perceived as a sign of adoption, which can affects the value of cryptocurrencies due to the network effect. (e.g. Cong, Li, and Wang (2020) and Sockin and Xiong (2020))

This paper studies the structure and drivers of cryptocurrency returns within the framework of examining crypto investors' demand.

Overview of Results

- Cryptocurrencies with similar size, trading volume, age, consensus mechanism, and token industries show significantly higher comovement.
- **The highest comovement is explained by exposure to similar investor bases proxied by cryptocurrencies trading locations.**
  a) Cryptocurrencies with a one-standard-deviation more overlapping exposure exhibit 0.223 standard deviations higher correlations.
  b) The effect increases in time-horizon and leads to a strong cross-predictability.

Overview of Results

- Cryptocurrencies with similar size, trading volume, age, consensus mechanism, and token industries show significantly higher comovement.
- **The highest comovement is explained by exposure to similar investor bases proxied by cryptocurrencies trading locations.**
  a) Cryptocurrencies with a one-standard-deviation more overlapping exposure exhibit 0.223 standard deviations higher correlations.
  b) The effect increases in time-horizon and leads to a strong cross-predictability.

Overview of Results

- Cryptocurrencies with similar size, trading volume, age, consensus mechanism, and token industries show significantly higher comovement.
- **The highest comovement is explained by exposure to similar investor bases proxied by cryptocurrencies trading locations.**
  a) Cryptocurrencies with a one-standard-deviation more overlapping exposure exhibit 0.223 standard deviations higher correlations.
  b) The effect increases in time-horizon and leads to a strong cross-predictability.

Overview of Results

- Cryptocurrencies with similar size, trading volume, age, consensus mechanism, and token industries show significantly higher comovement.
- **The highest comovement is explained by exposure to similar investor bases proxied by cryptocurrencies trading locations.**
  a) Cryptocurrencies with a one-standard-deviation more overlapping exposure exhibit 0.223 standard deviations higher correlations.
  b) The effect increases in time-horizon and leads to a strong cross-predictability.

Overview of Results

Potential Channels:

1) Unobservable Characteristics: evidence from new exchange listings and a quasi-natural experiment shows that unobservable characteristics do not seem to explain these patterns.

2) Commonalities in Crypto Investors' Demand: a strong exchange-specific component drives cryptocurrencies' order flows, even after controlling for the currency-specific flows.

3) The Network Externalities of Adoption: exposure to common demand shocks translates into 36.4% to 50.9% additional comovement for currencies that heavily rely on the network effect.

Overview of Results

Potential Channels:

1) Unobservable Characteristics: evidence from new exchange listings and a quasi-natural experiment shows that unobservable characteristics do not seem to explain these patterns.

2) Commonalities in Crypto Investors' Demand: a strong exchange-specific component drives cryptocurrencies' order flows, even after controlling for the currency-specific flows.

3) The Network Externalities of Adoption: exposure to common demand shocks translates into 36.4% to 50.9% additional comovement for currencies that heavily rely on the network effect.

Overview of Results

Potential Channels:

1) Unobservable Characteristics: evidence from new exchange listings and a quasi-natural experiment shows that unobservable characteristics do not seem to explain these patterns.

2) Commonalities in Crypto Investors' Demand: a strong exchange-specific component drives cryptocurrencies' order flows, even after controlling for the currency-specific flows.

3) The Network Externalities of Adoption: exposure to common demand shocks translates into 36.4% to 50.9% additional comovement for currencies that heavily rely on the network effect.

Related Literature

- **Broad economics of cryptocurrencies:** Harvey (2016); Raskin and Yermack (2018); Schilling and Uhlig (2019); Biais et al. (2019).
- **Mining activities and transaction costs:** Cong, He, and Li (2019); Pagnotta and Buraschi (2018); Easley, O'Hara, and Basu (2019).
- **Consensus mechanism and adoption problem:** Saleh (2020); Hinzen, John, and Saleh (2019a); Hinzen, John, and Saleh (2019b).
- **Analyzing blockchain transactions:** Foley, Karlsen, and Putnins (2018); Griffin and Shams (2020).
- **Initial Coin Offerings:** Howell, Niessner, and Yermack (2018); Lee, Li, and Shin (2019); Li and Mann (2020).
- **Market manipulation:** Gandal et al. (2018); Li, Shin, and Wang (2020); Cong et al. (2020).
- **Exchange frictions:** Kroeger and Sarkar (2017); Makarov and Schoar (2020).
- **Pricing Properties:** Liu and Tsyvinski (2019); Liu, Tsyvinski, and Wu (2019); Li and Yi (2018); Hu, Parlour, and Rajan (2018).
- **Network effect:** Cong, Li, and Wang (2020); Sockin and Xiong (2020); Gandal and Halaburda (2016).

Data

1. Trading and Price Data
   - *CoinAPI*: Hourly price and trading volume on near 200 exchanges
   - *Kaiko*: The entire order book for 26 exchanges
   - *CoinMarketCap*: Daily price and aggregate trading volume

2. Technological Features
   - E.g. coins versus tokens, cryptographic algorithm and consensus mechanism, token's industry, etc.

3. Social Media Data
   - 25 million currency-specific comments from Reddit

Data

1. Trading and Price Data
   - *CoinAPI*: Hourly price and trading volume on near 200 exchanges
   - *Kaiko*: The entire order book for 26 exchanges
   - *CoinMarketCap*: Daily price and aggregate trading volume

2. Technological Features
   - E.g. coins versus tokens, cryptographic algorithm and consensus mechanism, token's industry, etc.

3. Social Media Data
   - 25 million currency-specific comments from Reddit

Data

1. Trading and Price Data
   - *CoinAPI*: Hourly price and trading volume on near 200 exchanges
   - *Kaiko*: The entire order book for 26 exchanges
   - *CoinMarketCap*: Daily price and aggregate trading volume

2. Technological Features
   - E.g. coins versus tokens, cryptographic algorithm and consensus mechanism, token's industry, etc.

3. Social Media Data
   - 25 million currency-specific comments from Reddit

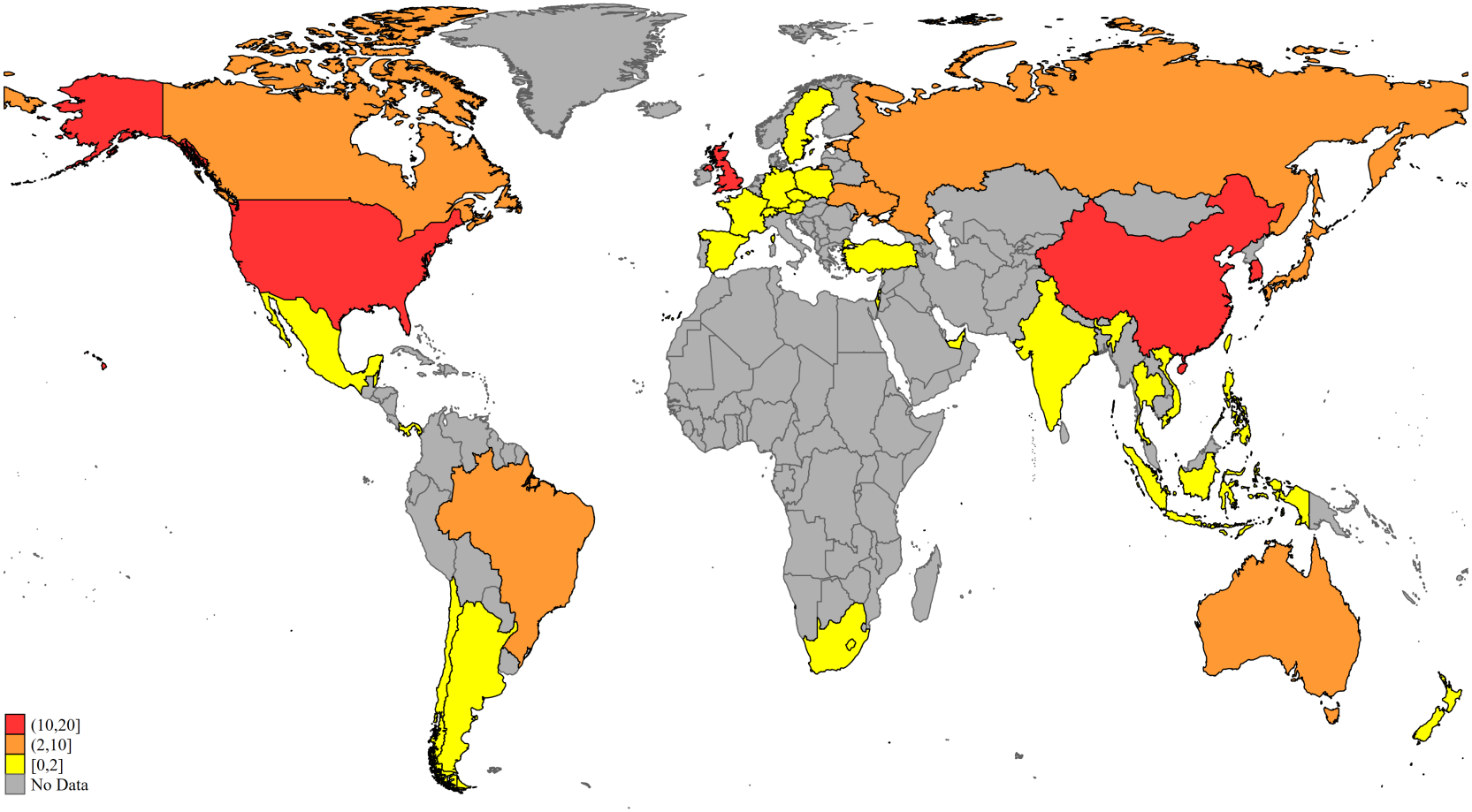
Number of Cryptocurrencies and Exchanges

Month	N Currencies	EW Daily Ret (%)	VW Daily Ret (%)	N Exchanges	Avg. Listing per Currency
2017M01	23	0.59	0.21	17	4.1
2017M02	33	-0.12	0.70	22	3.7
2017M03	35	2.54	0.48	30	6.5
2017M04	70	2.25	0.94	29	5.2
2017M05	69	3.76	2.99	28	4.6
2017M06	87	1.84	0.40	31	5.0
2017M07	135	-0.81	-0.17	32	3.9
2017M08	142	2.35	1.84	35	4.1
2017M09	168	-0.14	-0.34	43	4.4
2017M10	181	-0.19	0.68	40	4.3
2017M11	173	1.38	1.69	36	4.2
2017M12	218	4.23	2.40	47	4.9
2018M01	272	0.31	-0.39	57	5.2
2018M02	362	-0.84	-0.26	57	4.6
2018M03	263	-1.67	-1.62	63	5.6
2018M04	291	2.17	1.61	61	5.4
2018M05	335	-1.05	-0.73	60	5.0
2018M06	315	-1.50	-0.75	63	5.3
2018M07	306	-0.32	0.30	65	5.5
2018M08	305	-0.87	-0.60	66	6.1
2018M09	294	-0.13	-0.02	69	6.5
...					

Number of Cryptocurrencies and Exchanges

Month	N Currencies	EW Daily Ret (%)	VW Daily Ret (%)	N Exchanges	Avg. Listing per Currency
...					
2018M10	321	0.01	-0.29	71	6.3
2018M11	358	-1.95	-1.40	76	6.2
2018M12	339	-0.19	-0.04	79	7.0
2019M01	345	-0.22	-0.31	83	7.0
2019M02	328	0.57	0.53	90	7.6
2019M03	352	1.26	0.38	95	7.9
2019M04	374	0.16	0.66	114	8.9
2019M05	424	0.87	1.56	115	8.5
2019M06	432	0.25	0.57	113	8.6
2019M07	440	-0.42	-0.30	107	8.4
2019M08	442	-0.64	-0.29	108	8.4
2019M09	438	-0.40	-0.38	110	8.6
2019M10	437	0.36	0.38	142	10.1
2019M11	471	-0.30	-0.58	134	9.2
2019M12	454	-0.37	-0.21	134	9.7
2020M01	462	0.69	0.97	136	10.0
2020M02	486	0.34	-0.07	135	9.9
2020M03	485	-0.23	-0.52	130	9.6

Geographical Distribution of Exchanges



The Trading Environment

1. **Differences in Cryptocurrency Exchanges**
   - Geographical restrictions
   - Identity verification requirements
   - Limitations on deposits, withdrawals, and use of fiat currencies
   - Transaction fees

2. **Frictions Across Exchanges**
   - Cross-country capital restrictions
   - Slow confirmation and risks in withdrawal and deposit
   - KYC regulations and risks in disclosing sensitive information
     - $\rightarrow$ Investing in a limited set of exchanges

3. **Variation in Share of Cryptocurrencies on Different Exchanges**

The Trading Environment

1. **Differences in Cryptocurrency Exchanges**
   - Geographical restrictions
   - Identity verification requirements
   - Limitations on deposits, withdrawals, and use of fiat currencies
   - Transaction fees

2. **Frictions Across Exchanges**
   - Cross-country capital restrictions
   - Slow confirmation and risks in withdrawal and deposit
   - KYC regulations and risks in disclosing sensitive information
     - $\rightarrow$ Investing in a limited set of exchanges

3. **Variation in Share of Cryptocurrencies on Different Exchanges**

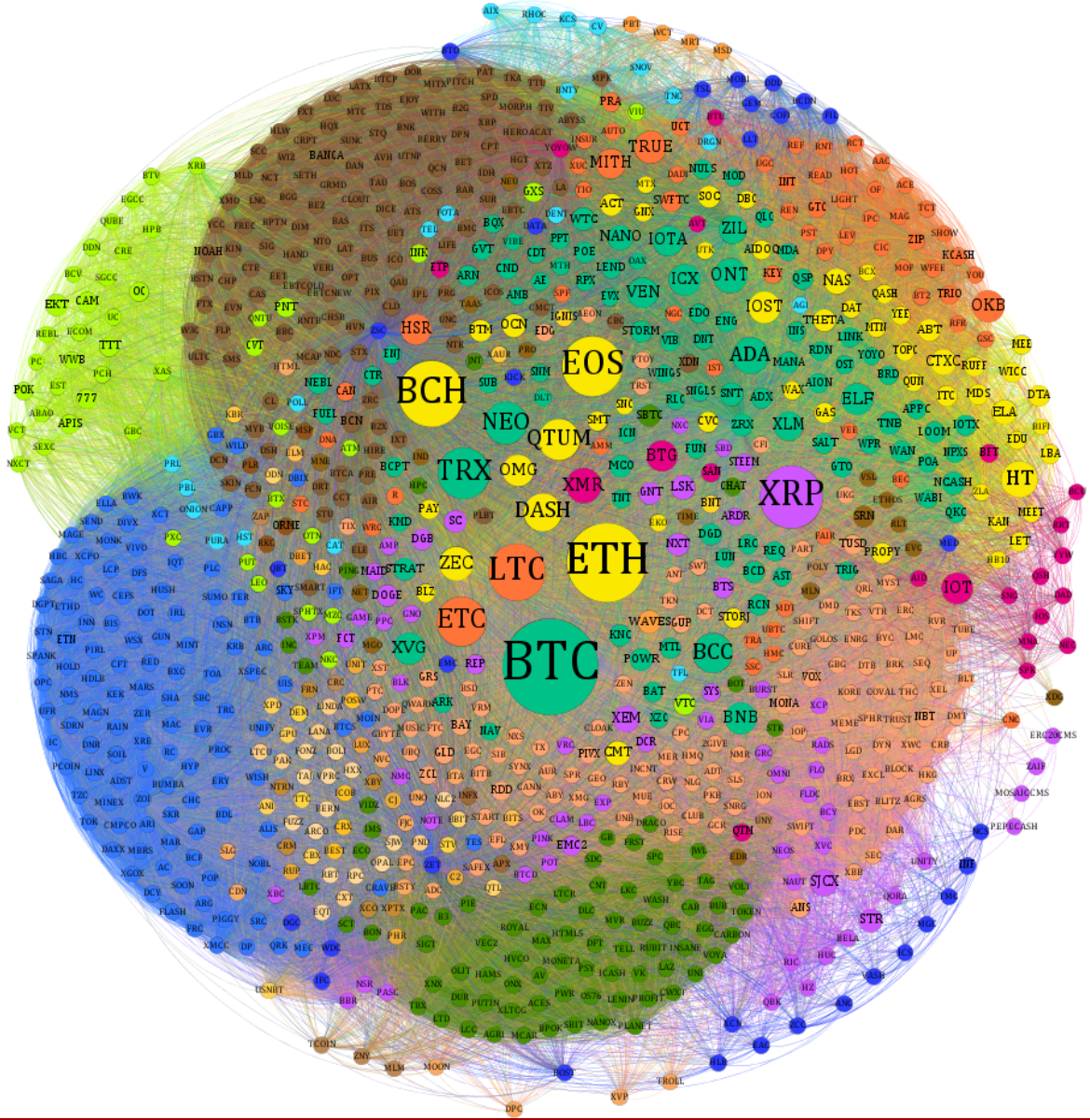
The Trading Environment

1. **Differences in Cryptocurrency Exchanges**
   - Geographical restrictions
   - Identity verification requirements
   - Limitations on deposits, withdrawals, and use of fiat currencies
   - Transaction fees

2. **Frictions Across Exchanges**
   - Cross-country capital restrictions
   - Slow confirmation and risks in withdrawal and deposit
   - KYC regulations and risks in disclosing sensitive information
     - $\rightarrow$ Investing in a limited set of exchanges

3. **Variation in Share of Cryptocurrencies on Different Exchanges**

Heterogeneity in *Connectivity*



Connectivity and Comovement

Pairwise setting similar to Anton and Polk (2014, JF):

$$Corr_{i,j,t} = \beta_0 + \beta_1 Connectivity_{i,j,t-1} + \beta^{Char} Similarity^{Char}_{i,j,t-1} + \delta_t + \varepsilon_{i,j,t}$$

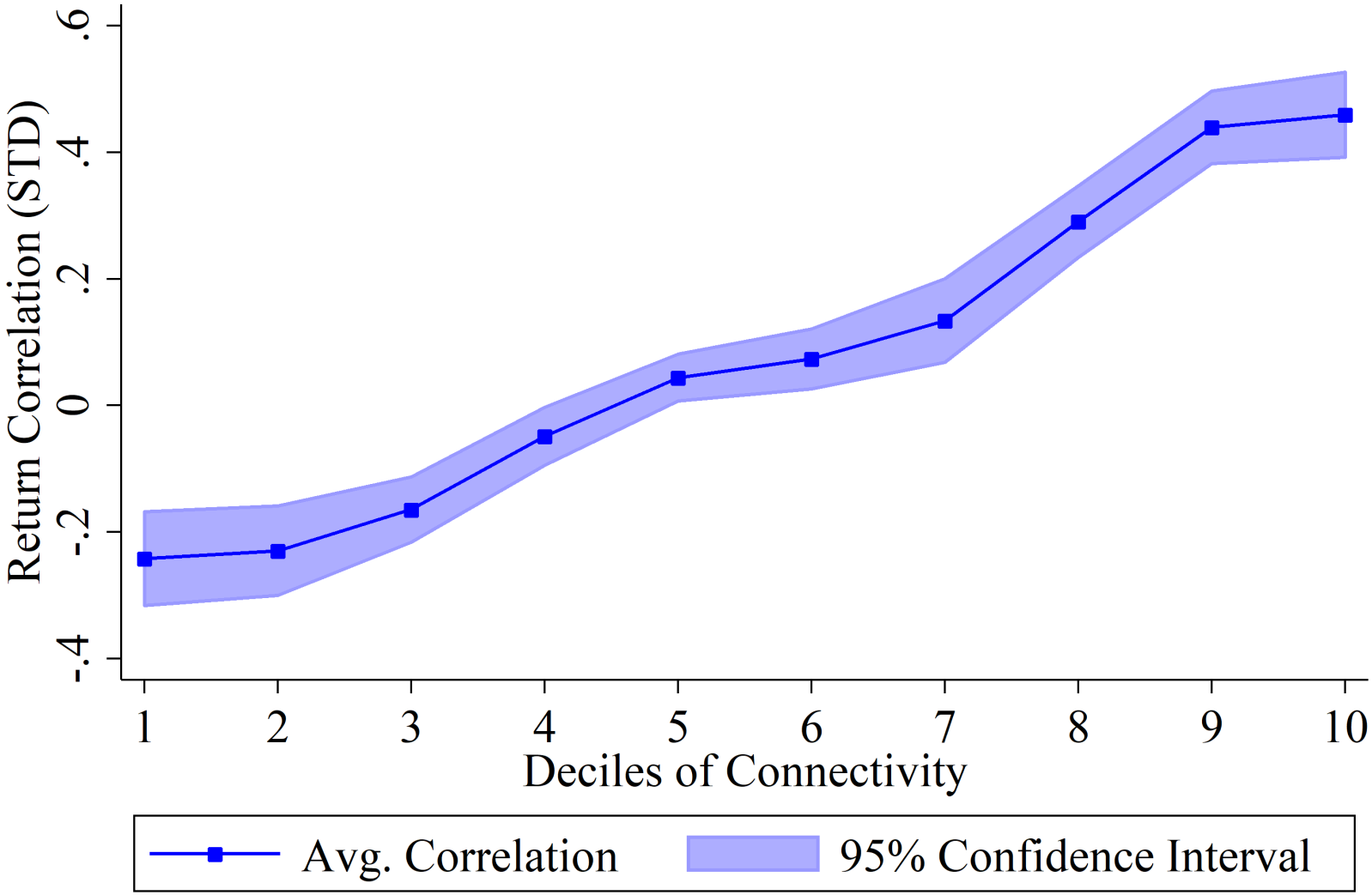
Connectivity and Comovement

	(1)	(2)	(3)	(4)	(5)	(6)
Connectivity	0.238***				0.223***	0.185***
	(20.95)				(20.68)	(21.62)
$\text{Similarity}^{\text{Size}}$		0.091***			0.045***	0.039***
		(12.60)			(5.59)	(5.09)
$\text{Similarity}^{\text{Volume}}$			0.101***		0.054***	0.052***
			(9.66)		(7.32)	(7.30)
$\text{Similarity}^{\text{NTrades}}$			0.020*		-0.007	-0.005
			(2.03)		(-0.83)	(-0.67)
$\text{Similarity}^{\text{Age}}$			0.045***		0.027**	0.020*
			(4.05)		(2.88)	(2.45)
$\text{Similarity}^{\text{NExch}}$			-0.007		-0.000	0.008
			(-0.18)		(-0.00)	(0.23)
$\text{Same}^{\text{Coin-Token}}$				0.031**	-0.010	-0.013
				(2.62)	(-0.98)	(-1.43)
L.Correlation						0.211***
						(17.27)
Observations	1,996,329	1,996,329	1,996,329	1,996,329	1,996,329	1,505,631
Within R^2	0.058	0.008	0.014	0.000	0.065	0.115
Dyadic Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

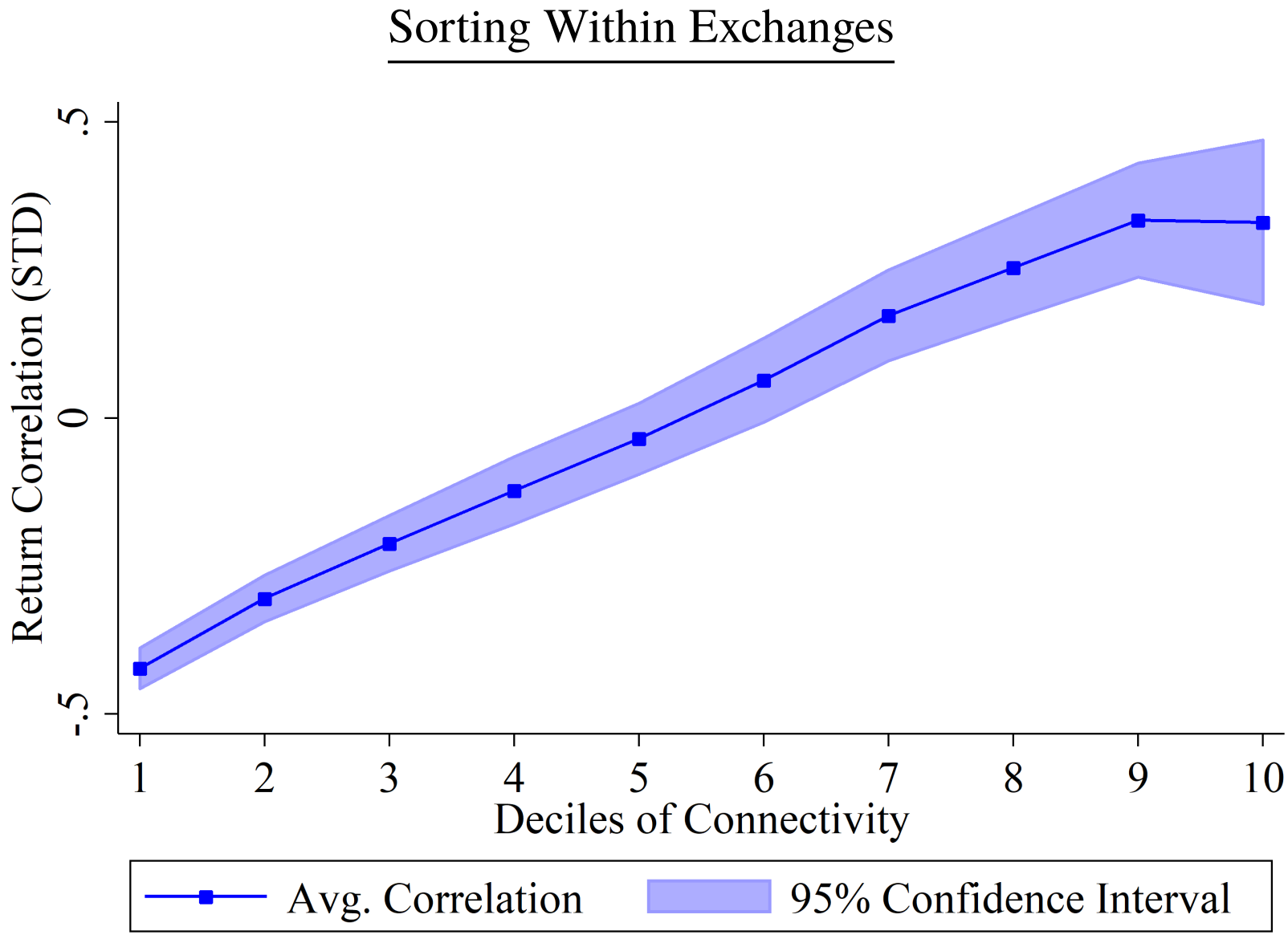
Connectivity and Comovement

	Coin Pairs				Token Pairs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connectivity	0.245***			0.204***	0.228***			0.208***
	(14.61)			(12.70)	(15.79)			(15.74)
$\text{Similarity}^{\text{Size}}$		0.088***		0.069***		0.085***		0.073***
		(6.06)		(5.45)		(9.65)		(10.40)
$\text{Similarity}^{\text{Volume}}$		0.078***		0.062***		0.090***		0.053***
		(5.26)		(4.59)		(8.46)		(7.23)
$\text{Similarity}^{\text{NTrades}}$		0.010		-0.021		0.041***		0.015*
		(0.54)		(-1.23)		(4.82)		(2.05)
$\text{Similarity}^{\text{Age}}$		0.038***		0.018		0.155***		0.105***
		(3.71)		(1.92)		(6.76)		(5.81)
$\text{Similarity}^{\text{NExch}}$		0.049		0.051		-0.289***		-0.251***
		(1.19)		(1.28)		(-13.43)		(-13.27)
$\text{Same}^{\text{ProofType}}$			0.110**	0.057*				
			(2.98)	(2.18)				
$\text{Same}^{\text{HashAlgo}}$			0.022	-0.010				
			(0.47)	(-0.20)				
$\text{Same}^{\text{Fork}}$			-0.057	-0.016				
			(-0.63)	(-0.33)				
$\text{Same}^{\text{Mineable}}$			0.004	0.005				
			(0.19)	(0.39)				
$\text{Same}^{\text{Platform}}$							0.108**	0.047
							(2.65)	(1.50)
$\text{Same}^{\text{Industry}}$							0.127**	0.074*
							(3.07)	(2.24)
$\text{Same}^{\text{TokenType}}$							-0.078	-0.055
							(-1.37)	(-1.25)

Connectivity and Comovement



Connectivity and Comovement



Fama-MacBeth Regression on Connected Portfolio Returns

	12hr	**1d**	**2d**	**3d**	**4d**
Connected Ret	0.45***	0.47***	0.53***	0.62***	0.70***
	(14.04)	(10.31)	(8.51)	(8.99)	(8.92)
Constant	0.0032***	0.0059***	0.0079*	0.014**	0.018*
	(4.08)	(3.61)	(2.48)	(2.77)	(2.54)
Observations	8226683	8213276	8200376	8191592	8185746
R^2	0.014	0.016	0.017	0.018	0.019

	5d	**6d**	**1w**	**2w**	**4w**
Connected Ret	0.72***	0.78***	0.75***	0.76***	0.82***
	(8.25)	(8.04)	(7.19)	(5.08)	(5.15)
Constant	0.023*	0.029*	0.034*	0.055	0.12
	(2.52)	(2.54)	(2.46)	(1.73)	(1.53)
Observations	8181803	8179551	8177308	8157032	8063219
R^2	0.019	0.019	0.020	0.024	0.022

Order Flows

	(1)	(2)	(3)	(4)	(5)
$OIBNUM^{Cur}$	0.125**			0.0925*	0.102*
	(2.96)			(2.45)	(2.35)
$OIBNUM^{Exch}$		0.309***		0.299***	0.298***
		(7.11)		(5.85)	(5.72)
$OIBNUM^{Mkt}$			0.0921*	-0.00342	-0.00424
			(2.24)	(-0.16)	(-0.19)
$L.OIBNUM^{Cur}$					-0.00791
					(-0.77)
$F.OIBNUM^{Cur}$					-0.0126
					(-1.83)
Curr-Exch FE	Yes	Yes	Yes	Yes	Yes
Observations	111,528	111,528	111,528	111,528	107,899
R^2	0.021	0.102	0.013	0.110	0.111
Curr & Exch Cluster	Yes	Yes	Yes	Yes	Yes

Shut Down of Chinese Crypto Exchanges

- The Chinese government shut down all Chinese crypto exchanges in September 2017.
- The shutdown created an exogenous shock to certain cryptocurrencies trading locations and, hence, to their connectivity.
- I use the shock to construct an instrument for changes in connectivity.

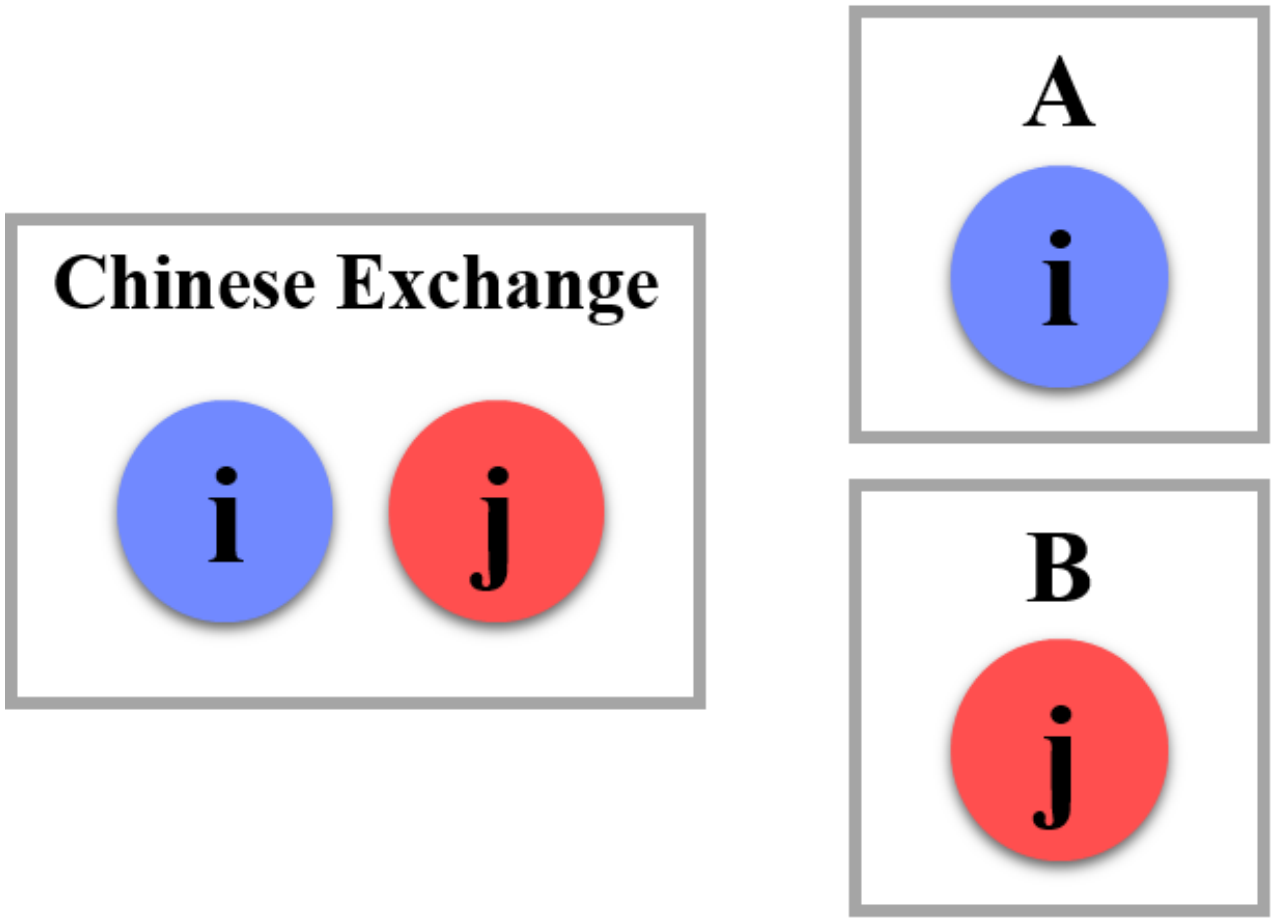
Shut Down of Chinese Crypto Exchanges

- The Chinese government shut down all Chinese crypto exchanges in September 2017.
- The shutdown created an exogenous shock to certain cryptocurrencies trading locations and, hence, to their connectivity.
- I use the shock to construct an instrument for changes in connectivity.

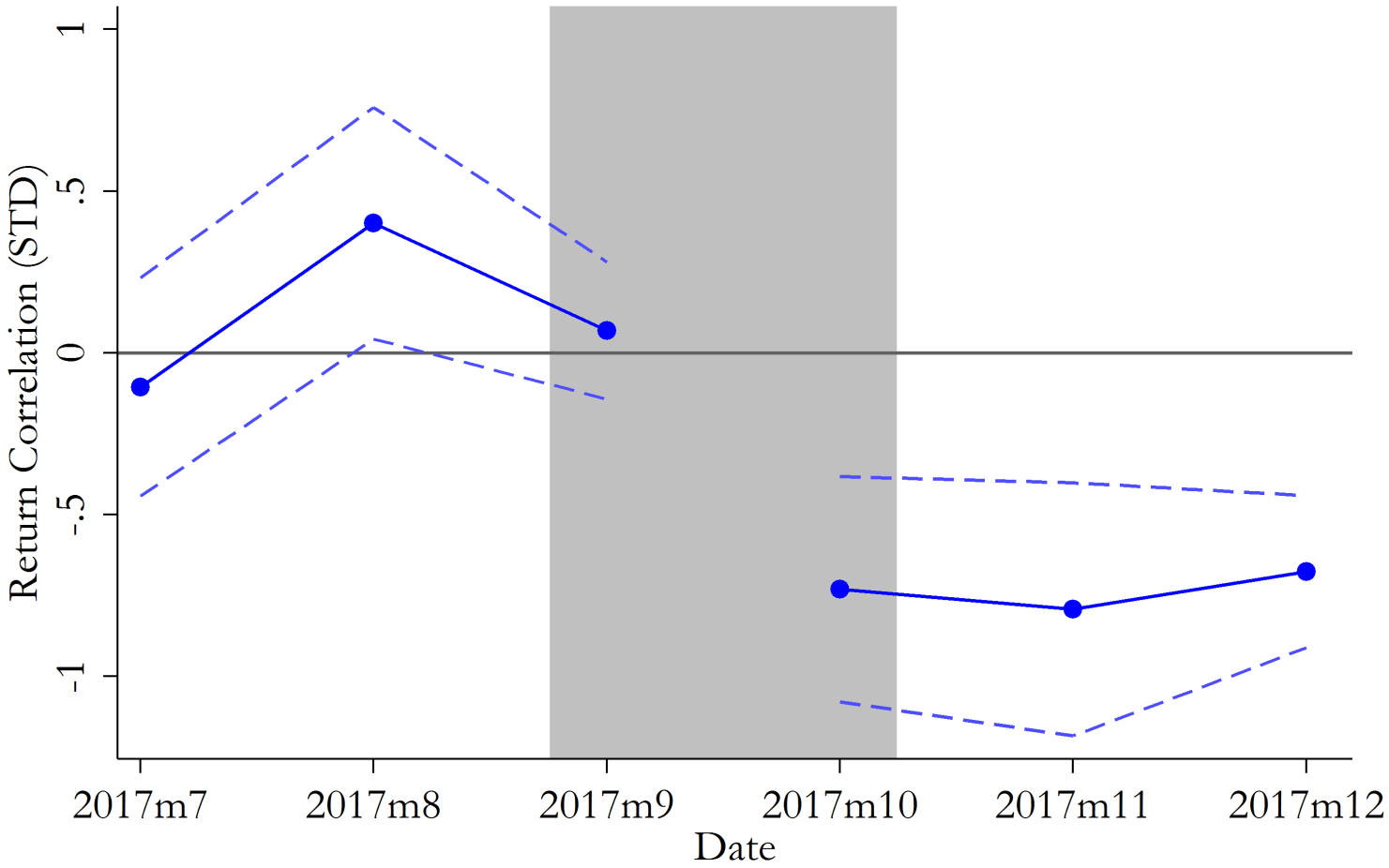
Shut Down of Chinese Crypto Exchanges

- The Chinese government shut down all Chinese crypto exchanges in September 2017.
- The shutdown created an exogenous shock to certain cryptocurrencies trading locations and, hence, to their connectivity.
- I use the shock to construct an instrument for changes in connectivity.

Currencies Affected by the Shock



Changes in Pairwise Correlations



2SLS Estimation

	ΔCorr	ΔCorr
ΔConnectivity	0.188***	0.174**
	(3.34)	(2.78)
ΔSameVol		0.032
		(1.09)
Cohort FE	Yes	Yes
Observations	40,887	40,887
Dyadic Clustering	Yes	Yes
First-Stage F statistics	21.42	21.22

The Network Effect

- In addition to investors, users and developers have a demand for holding cryptocurrencies.
- The value of cryptocurrencies can be attributed to the network effect of adoption by these users and developers.
  - Cong, Li, and Wang (2019); Sockin and Xiong (2018); Li and Mann (2018); Gandal and Halaburda (2016).
- The crypto community also considers adoption and community building as a key source of cryptocurrencies' value.
  - Many perceive buying pressures on crypto exchanges as a sign of user adoption.
- Demand pressures can have an amplified effect on cryptocurrencies because they may be interpreted as a sign of "adoption."

Quantifying the Importance of Network Effect

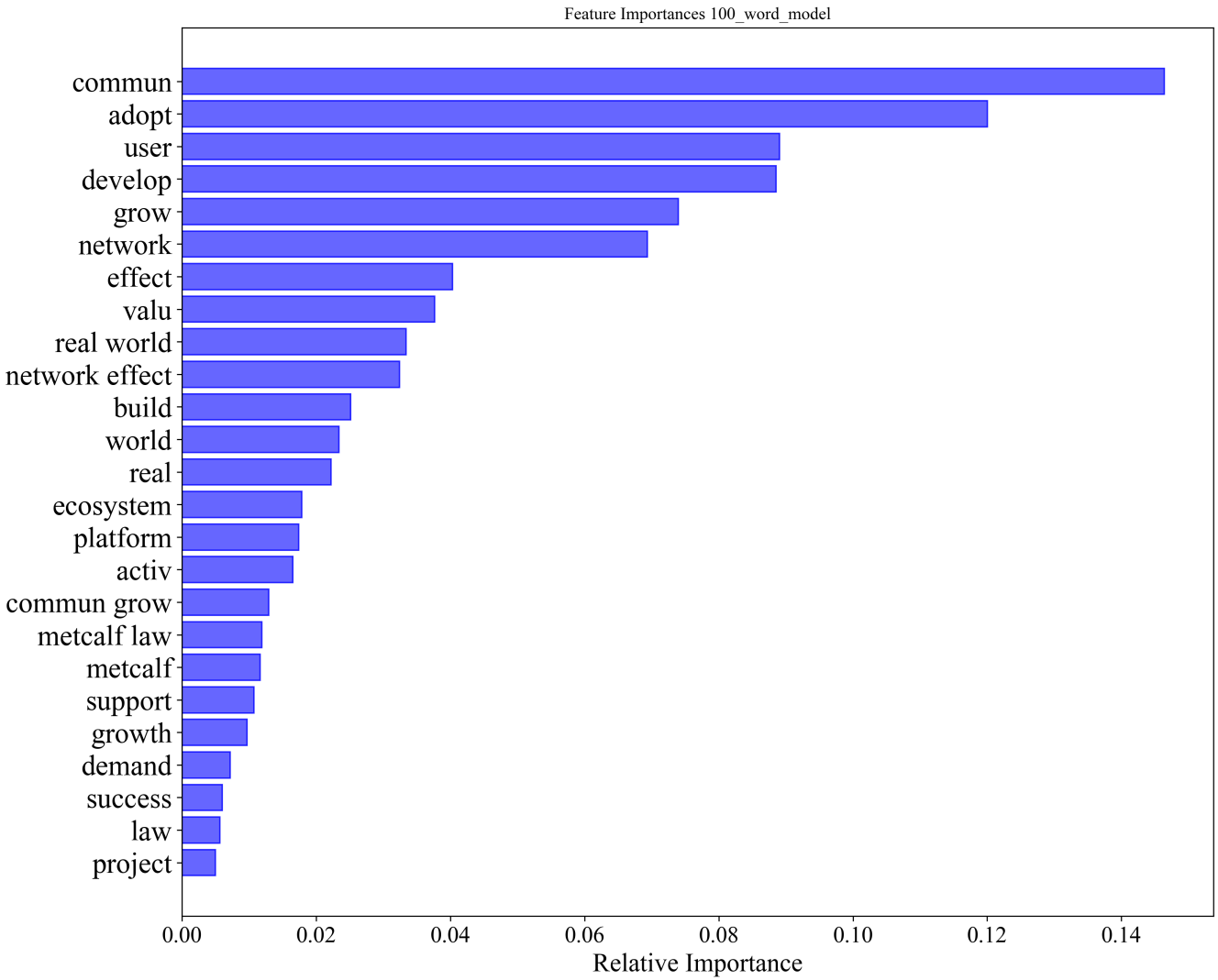
I use 25 million currency-specific comments on Reddit:

1. reading and labeling 10,000 comments as a training sample.
2. fitting a random forest model to extract important features that distinguishes the comments.
3. feeding the rest of 25M comments into the model for labeling.
4. quantifying the percentage of comments that are labeled *1* each month for each cryptocurrency.

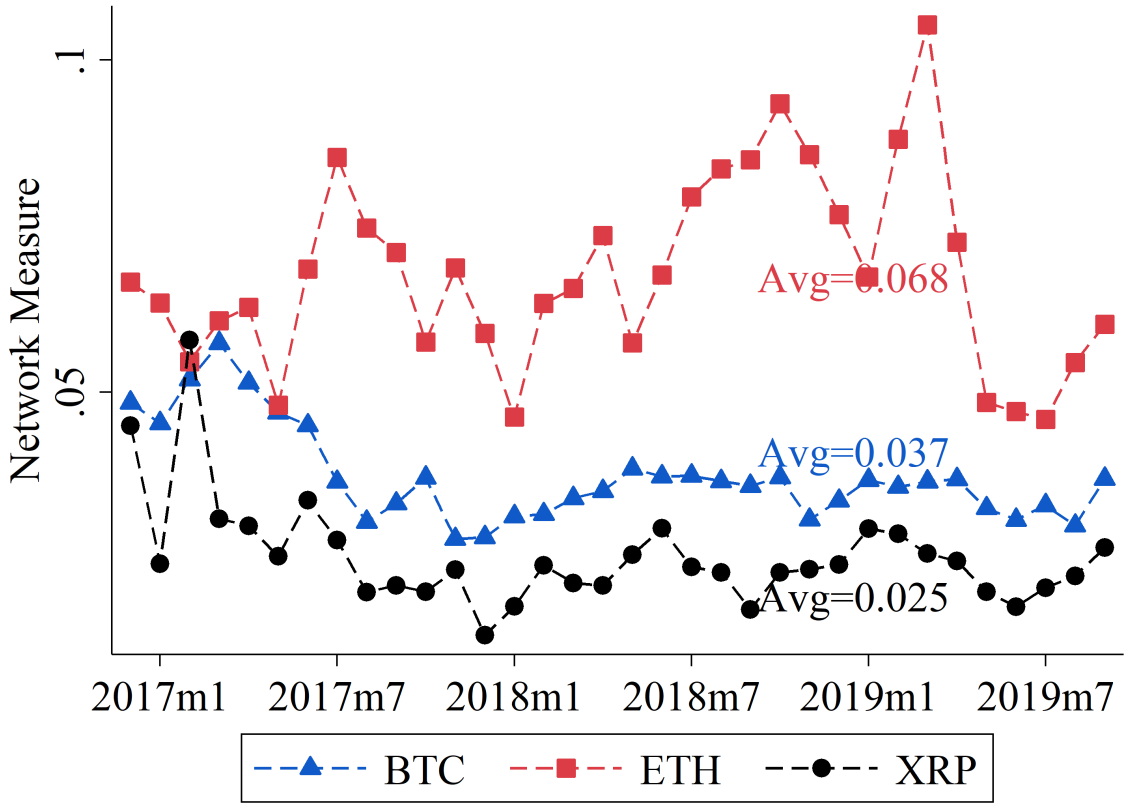
Examples of Comments

- "You should look at community support and number of developers working on projects for a certain platform. There is no other project with network effects even close to ethereum."
- "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."
- "If you value eth using metcalfs law it's obvious why it's up so much as number of users has gone up so much. People calling it a bubble just don't get it sure price has gone up so much but users and transactions has as well"
- "Bitcoin is growing at its fastest pace in history in terms of network effect/user adoption. Bull run is not over until BTC is past gold/10 trillion."

Random Forest Feature Importance



The Network Measure for Major Currencies



For example, the percentage of Ethereum comments that include the terms "network effect," "user adoption," "community building," and "user demand" are 6, 7.7, 13.3, and 17.3 times that of Ripple, respectively.

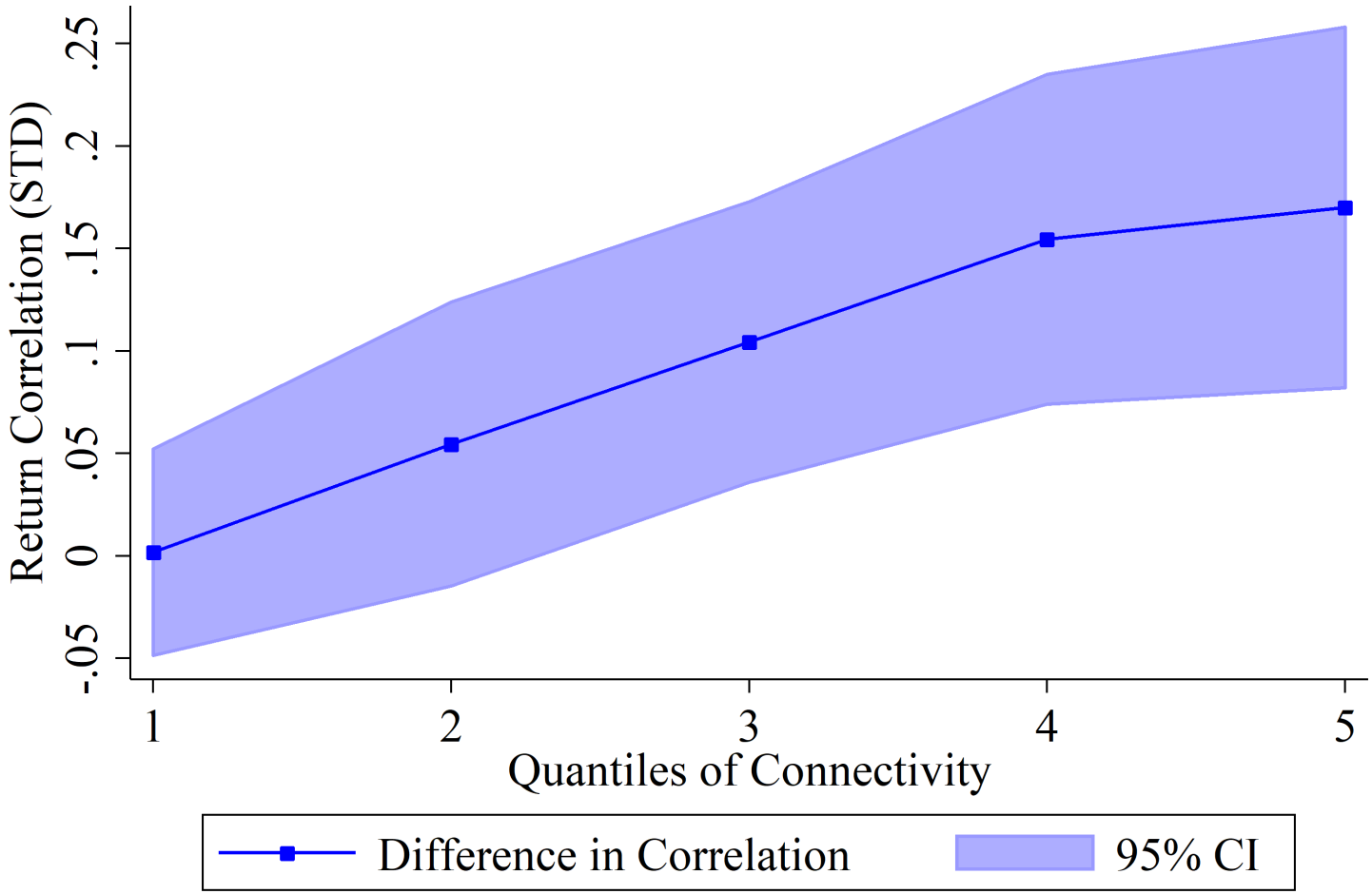
The Network Measure for Major Currencies

Name	Ticker	AvgNetworkMeasure	PlatToken
Ethereum	ETH	0.068	1
Ethereum Classic	ETC	0.060	1
Cardano	ADA	0.057	1
Tezos	XTZ	0.057	1
EOS	EOS	0.052	1
Stellar	XLM	0.048	1
Monero	XMR	0.043	0
Chainlink	LINK	0.043	0
Tron	TRX	0.039	1
Bitcoin	BTC	0.037	0
Bitcoin Cash	BCH	0.034	0
Litecoin	LTC	0.025	0
Ripple	XRP	0.025	0
Binance Coin	BNB	0.018	0

Amplifying Effect of Network Externalities

	(1)	(2)	(3)	(4)	(5)
Connectivity	0.165***	0.165***	0.135***	0.116**	0.149***
	(9.16)	(9.13)	(5.58)	(3.06)	(6.45)
Hi_NetwEffect	0.102***	0.102***	0.101***	0.074*	0.161
	(3.47)	(3.46)	(3.48)	(2.17)	(1.61)
Connectivity*Hi_NetwEffect	0.060***	0.060***	0.054**	0.059**	0.117**
	(3.33)	(3.33)	(3.26)	(3.00)	(3.26)
$\text{Similarity}^{\text{Size}}$	0.060***	0.059***	0.062***	0.066***	0.061***
	(3.42)	(3.40)	(3.82)	(3.63)	(3.66)
$\text{Similarity}^{\text{Volume}}$	0.063***	0.063***	0.065***	0.065***	0.063***
	(4.16)	(4.17)	(4.40)	(3.97)	(4.19)
$\text{Similarity}^{\text{NTrades}}$	-0.025	-0.025	-0.016	-0.011	-0.016
	(-1.31)	(-1.31)	(-0.95)	(-0.54)	(-0.92)
$\text{Similarity}^{\text{Age}}$	0.045**	0.044**	0.048**	0.071***	0.049**
	(3.15)	(3.13)	(3.28)	(4.01)	(3.29)
$\text{Similarity}^{\text{NExch}}$	0.131**	0.131**	0.147**	0.157**	0.151**
	(3.14)	(3.13)	(2.88)	(2.83)	(2.91)
$\text{Same}^{\text{Coin-Token}}$	-0.015	-0.016	-0.015		-0.022
	(-1.20)	(-1.22)	(-1.22)		(-1.58)
$\text{Similarity}^{\text{NComments}}$		0.003	0.004	-0.007	0.005
		(0.44)	(0.53)	(-0.96)	(0.67)
Constant	-0.021	-0.021	-0.036	-0.048	-0.009

Additional Comovement of High-Network Currencies by Quantiles of Connectivity



Conclusion

- Cryptocurrencies return structure is mainly explained by exposure to similar investor clientele proxied by their trading locations. This effect increases in time-horizon and leads to a strong cross-predictability.
- **Unobservable characteristics** do not seem to explain this effect, but it reflects a strong **exchange-specific component in crypto investors' demand**, which holds even after controlling for the currency-specific flows.
- These demand shocks seem to be largely amplified through **the network effect**, potentially because they are perceived as a sign of user adoption.
- Understanding the demand side of the market is a key to understanding cryptocurrency prices.