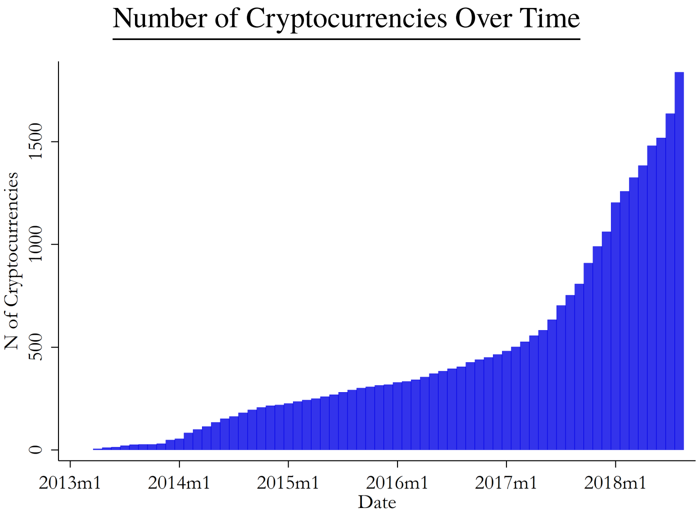
# What Drives the Covariation of Cryptocurrency Returns?

**Amin Shams**
**The Ohio State University**

**January 4, 2020**

# Motivation


Number of Cryptocurrencies Over Time
N of Cryptocurrencies
0
500
1000
1500
2013m1
2014m1
2015m1
2016m1
2017m1
2018m1
Date

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Motivation

We know very little about this market.

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

**This paper studies the structure and drivers of cryptocurrency returns and sheds light on these questions by examining the trading behavior of crypto investors.**

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

# Characterizing Cryptocurrencies

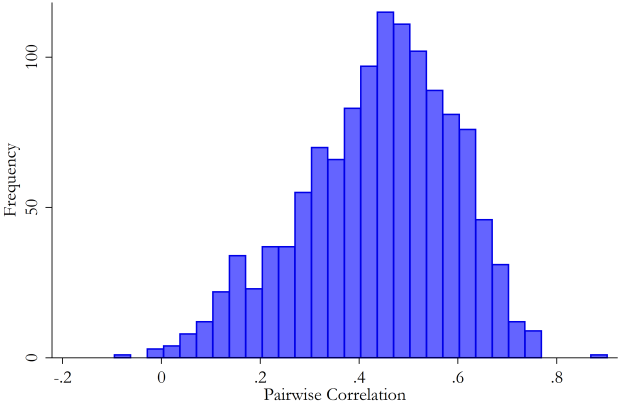
1. Medium of exchange
   - Off the platform (e.g. Bitcoin)
   - On the platform (e.g. Filecoin)

2. In addition to investors, users and developers have a demand for holding cryptocurrencies.

3. Underlying value depends on the network effect.
   - "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."
   - "More developer activity and use cases = higher user adoption = more demand for req = higher req price"
   - "How many users can Coinbase onboard everyday? The more people that own 1 LTC, the faster the value grows."

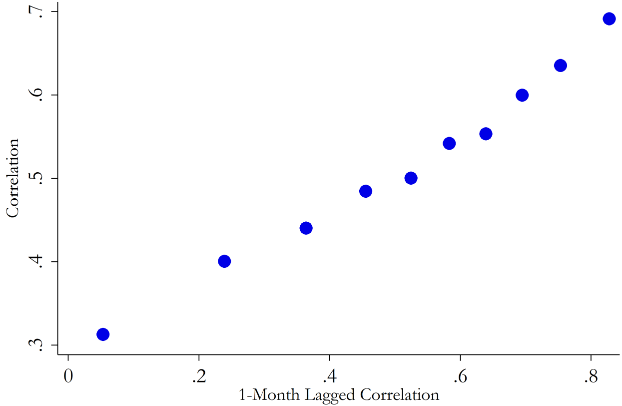
# Empirical Facts

1. Wide variation in the pairwise correlation of cryptocurrency returns



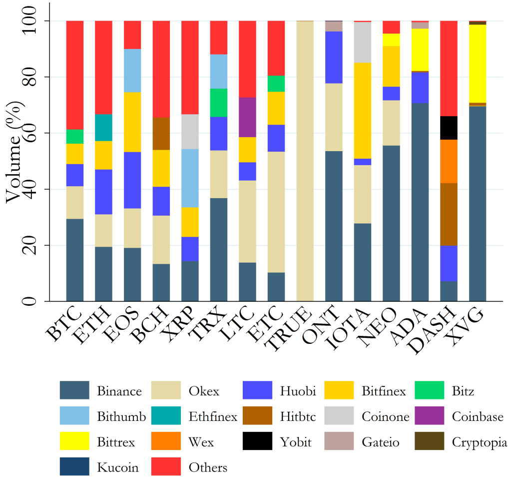
# Empirical Facts

1. ... and this variation is persistent over time.



# Empirical Facts

2. Wide variation in trading platforms of cryptocurrencies



# Overview of Results

1. **Cryptocurrencies with a similar investor base comove substantially more than currencies with different investors.**

   a) One standard deviation higher "connectivity" is associated with approximately 0.2 standard deviations higher correlations.

   b) This effect cannot be explained by similarities in technological features or other characteristics.

   c) Exogenous changes in the investor base cause significant changes in comovement.

   d) The effect increases in time-horizon and leads to a strong cross-predictability.

# Overview of Results

1. **Cryptocurrencies with a similar investor base comove substantially more than currencies with different investors.**

    a) One standard deviation higher "connectivity" is associated with approximately 0.2 standard deviations higher correlations.

    b) This effect cannot be explained by similarities in technological features or other characteristics.

    c) Exogenous changes in the investor base cause significant changes in comovement.

    d) The effect increases in time-horizon and leads to a strong cross-predictability.

# Overview of Results

1. **Cryptocurrencies with a similar investor base comove substantially more than currencies with different investors.**

   a) One standard deviation higher "connectivity" is associated with approximately 0.2 standard deviations higher correlations.

   b) This effect cannot be explained by similarities in technological features or other characteristics.

   c) Exogenous changes in the investor base cause significant changes in comovement.

   d) The effect increases in time-horizon and leads to a strong cross-predictability.

# Overview of Results

1. **Cryptocurrencies with a similar investor base comove substantially more than currencies with different investors.**

   a) One standard deviation higher "connectivity" is associated with approximately 0.2 standard deviations higher correlations.

   b) This effect cannot be explained by similarities in technological features or other characteristics.

   c) Exogenous changes in the investor base cause significant changes in comovement.

   d) The effect increases in time-horizon and leads to a strong cross-predictability.

# Overview of Results

1. **Cryptocurrencies with a similar investor base comove substantially more than currencies with different investors.**

   a) One standard deviation higher "connectivity" is associated with approximately 0.2 standard deviations higher correlations.

   b) This effect cannot be explained by similarities in technological features or other characteristics.

   c) Exogenous changes in the investor base cause significant changes in comovement.

   d) The effect increases in time-horizon and leads to a strong cross-predictability.

# Overview of Results

2. **The network effect plays an important role in explaining the magnitude of the results.**

   a) Exposure to similar investor bases translates into 40 to 50% additional comovement for currencies that heavily rely on the network externalities arising from user and developer participation.

   b) More network-based cryptocurrencies exhibit higher volatility.

# Overview of Results

2. **The network effect plays an important role in explaining the magnitude of the results.**

    a) Exposure to similar investor bases translates into 40 to 50% additional comovement for currencies that heavily rely on the network externalities arising from user and developer participation.

    b) More network-based cryptocurrencies exhibit higher volatility.

# Overview of Results

2. **The <u>network effect</u> plays an important role in explaining the magnitude of the results.**

   a) Exposure to similar investor bases translates into 40 to 50% additional comovement for currencies that heavily rely on the network externalities arising from user and developer participation.

   b) More network-based cryptocurrencies exhibit higher volatility.

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

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

# Related Literature

**2. Literature on return comovement:** Barberis, Shleifer, and Wurgler (2005), Greenwood (2007), Coval and Stafford (2007), Greenwood and Thesmar (2011), Anton and Polk (2014), and Bartram et al. (2015).

**3. Literature on cross-listing and market fragmentation:** Werner and Kleidon (1996), Froot and Dabora (1999), Chan, Hameed, and Lau (2003), De Jong, Rosenthal, and Van Dijk (2009), and Brealey, Cooper, and Kaplanis (2009).

**This paper examines a novel channel that amplifies the price impact of common demand shocks.**

# Related Literature

**2. Literature on return comovement:** Barberis, Shleifer, and Wurgler (2005), Greenwood (2007), Coval and Stafford (2007), Greenwood and Thesmar (2011), Anton and Polk (2014), and Bartram et al. (2015).

**3. Literature on cross-listing and market fragmentation:** Werner and Kleidon (1996), Froot and Dabora (1999), Chan, Hameed, and Lau (2003), De Jong, Rosenthal, and Van Dijk (2009), and Brealey, Cooper, and Kaplanis (2009).

**This paper examines a novel channel that amplifies the price impact of common demand shocks.**

# Related Literature

**2. Literature on return comovement:** Barberis, Shleifer, and Wurgler (2005), Greenwood (2007), Coval and Stafford (2007), Greenwood and Thesmar (2011), Anton and Polk (2014), and Bartram et al. (2015).

**3. Literature on cross-listing and market fragmentation:** Werner and Kleidon (1996), Froot and Dabora (1999), Chan, Hameed, and Lau (2003), De Jong, Rosenthal, and Van Dijk (2009), and Brealey, Cooper, and Kaplanis (2009).

**This paper examines a novel channel that amplifies the price impact of common demand shocks.**

# Main Testable Hypotheses

1. Cryptocurrencies with similar investor bases should exhibit strong comovement in returns and order imbalance beyond what can be explained by their characteristics and technology.
   - Exogenous changes in the investor base should cause changes in comovement.

2. This effect should be larger for cryptocurrencies that derive more value from the network effect because of the additional price impact of the common demand shocks.

# Main Testable Hypotheses

1. Cryptocurrencies with similar investor bases should exhibit strong comovement in returns and order imbalance beyond what can be explained by their characteristics and technology.
   - Exogenous changes in the investor base should cause changes in comovement.

2. This effect should be larger for cryptocurrencies that derive more value from the network effect because of the additional price impact of the common demand shocks.

# Main Testable Hypotheses

1. Cryptocurrencies with similar investor bases should exhibit strong comovement in returns and order imbalance beyond what can be explained by their characteristics and technology.
   - Exogenous changes in the investor base should cause changes in comovement.

2. This effect should be larger for cryptocurrencies that derive more value from the network effect because of the additional price impact of the common demand shocks.

# Data

1. Trading and Price Data
   - *CoinAPI*: Minute-level price and trading volume on 70 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
   - 12 million currency-specific comments from Reddit

# Data

1. Trading and Price Data
   - *CoinAPI*: Minute-level price and trading volume on 70 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
   - 12 million currency-specific comments from Reddit

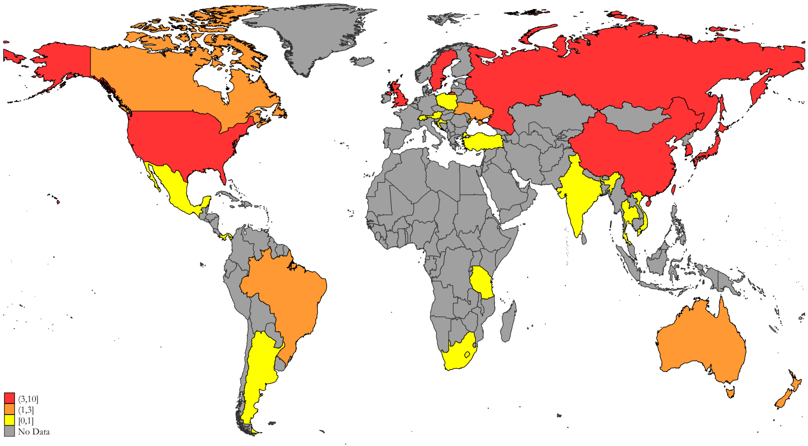
# Data

1. Trading and Price Data
   - *CoinAPI*: Minute-level price and trading volume on 70 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
   - 12 million currency-specific comments from Reddit

# Number of Cryptocurrencies Over Time

| Month | N Currencies | EW Daily Ret (%) | VW Daily Ret (%) |
|---|---|---|---|
| 2017M01 | 50 | 0.60 | 0.03 |
| 2017M02 | 59 | 0.21 | 0.86 |
| 2017M03 | 237 | 3.52 | 2.14 |
| 2017M04 | 132 | 1.74 | 2.21 |
| 2017M05 | 133 | 2.96 | 3.99 |
| 2017M06 | 193 | 1.45 | 1.52 |
| 2017M07 | 218 | -0.86 | 0.40 |
| 2017M08 | 237 | 1.84 | 3.04 |
| 2017M09 | 275 | -0.03 | 0.20 |
| 2017M10 | 264 | -0.37 | 1.37 |
| 2017M11 | 315 | 1.34 | 3.71 |
| 2017M12 | 372 | 3.92 | 4.70 |
| 2018M01 | 549 | -0.06 | 0.50 |
| 2018M02 | 499 | -0.92 | 0.41 |
| 2018M03 | 512 | -1.87 | -1.22 |
| 2018M04 | 599 | 2.17 | 2.57 |
| 2018M05 | 574 | -0.92 | -0.38 |
| 2018M06 | 554 | -1.58 | -0.67 |

# 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**

# Proxy for Exposure to Similar Investor Base

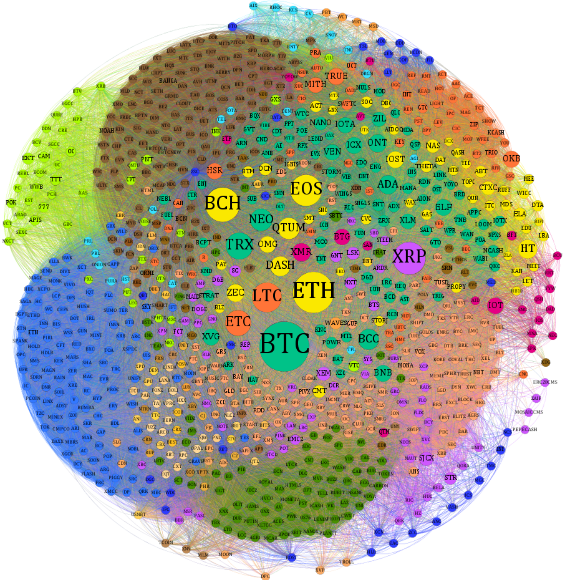
A pairwise *Connectivity* measure:

$$Connectivity_{i,j,t} = 1 - \frac{1}{2}\sum_{k=1}^{K} |p_{i,k,t} - p_{j,k,t}|$$

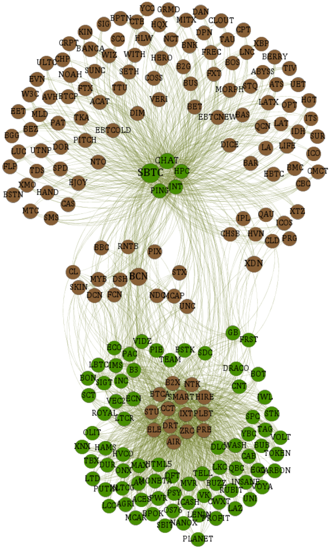
where

$$p_{i,k,t} = \frac{V_{i,k,t}}{\sum_{n=1}^{K} V_{i,n,t}}$$

# Heterogeneity in *Connectivity*



# Within Cluster Heterogeneity

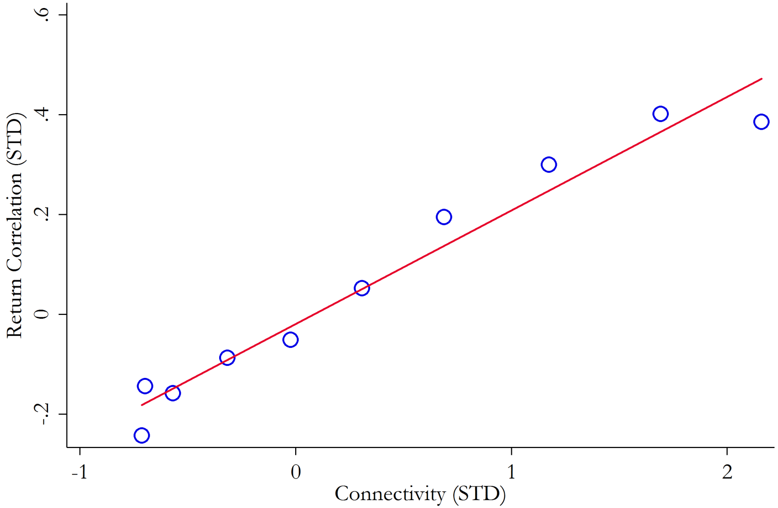


# Connectivity and Comovement

Pairwise Setting:

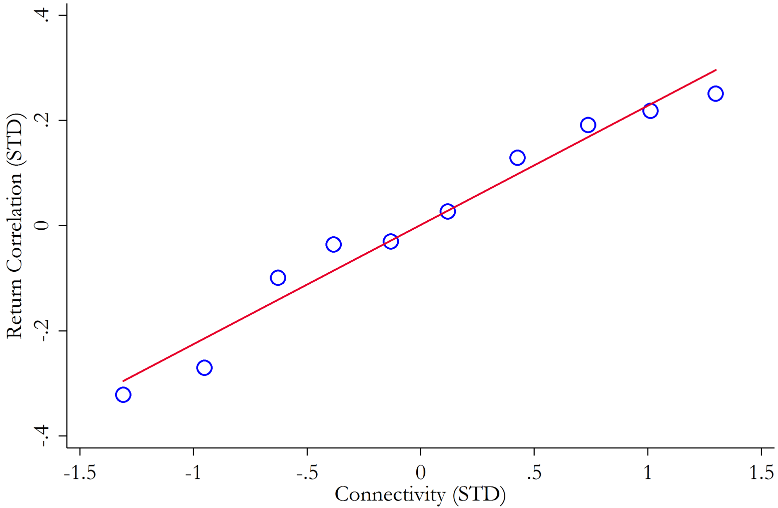
$$Corr_{i,j,t} = \beta_0 + \beta_1 Connectivity_{i,j,t-1} + \beta^{Char} Similarity^{Char}_{i,j,t-1} + \delta_t + \varepsilon_{i,j,t}$$

# Connectivity and Comovement



# Connectivity and Comovement

## Sorting Within Exchanges



# Connectivity and Comovement

| | All Currencies | | | Large Currencies | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Connectivity | 0.189*** | 0.174*** | 0.172*** | 0.213*** | 0.190*** | 0.187*** |
| | (20.21) | (19.72) | (19.82) | (11.36) | (12.05) | (12.22) |
| $\text{Similarity}^{\text{Volume}}$ | | 0.068*** | 0.068*** | | 0.204*** | 0.199*** |
| | | (7.67) | (7.58) | | (4.00) | (3.92) |
| $\text{Similarity}^{\text{NExch}}$ | | 0.040* | 0.039* | | 0.057* | 0.057* |
| | | (2.30) | (2.29) | | (2.51) | (2.54) |
| $\text{Similarity}^{\text{CoinToken}}$ | | | 0.037** | | | 0.042 |
| | | | (2.99) | | | (1.72) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 447771 | 444592 | 444592 | 62549 | 61537 | 61537 |
| Adjusted $R^2$ | .179 | .185 | .185 | .176 | .186 | .187 |
| Dyadic Clustering | Yes | Yes | Yes | Yes | Yes | Yes |

# Technological Features

| | Coin Pairs | | | Token Pairs | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Connectivity | 0.196*** | | 0.190*** | 0.194*** | | 0.180*** |
| | (11.99) | | (11.32) | (16.97) | | (16.21) |
| $\text{Similarity}^{\text{ProofType}}$ | | 0.079* | 0.063* | | | |
| | | (2.29) | (2.06) | | | |
| $\text{Similarity}^{\text{HashAlgo}}$ | | 0.055 | 0.028 | | | |
| | | (1.73) | (0.98) | | | |
| $\text{Similarity}^{\text{Fork}}$ | | 0.081 | 0.086 | | | |
| | | (1.21) | (1.43) | | | |
| $\text{Similarity}^{\text{Volume}}$ | | | 0.035* | | | 0.076*** |
| | | | (2.38) | | | (6.91) |
| $\text{Similarity}^{\text{Platform}}$ | | | | | 0.032 | 0.004 |
| | | | | | (1.07) | (0.17) |
| $\text{Similarity}^{\text{Industry}}$ | | | | | 0.121** | 0.098** |
| | | | | | (3.07) | (2.97) |
| $\text{Similarity}^{\text{TokenType}}$ | | | | | -0.060 | -0.044 |
| | | | | | (-1.89) | (-1.63) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 82588 | 82588 | 82588 | 111386 | 111386 | 111386 |
| Adjusted $R^2$ | 0.180 | 0.143 | 0.182 | 0.206 | 0.168 | 0.210 |
| Double Cluster | Yes | Yes | Yes | Yes | Yes | Yes |

# Connected Portfolio Returns

Summarizing the returns of all currencies connected to currency $i$:

$$R_{i,t}^{Con} = \sum_{j=1}^{N} w_{j,t} R_{j,t}$$

$$w_{j,t} = \frac{Connectivity_{i,j,t-1} Volume_{j,t-1}}{\sum_{n=1}^{N} Connectivity_{i,n,t-1} Volume_{n,t-1}}$$

# Fama-MacBeth Regression of Returns on Connected Portfolio Returns

| | 12hr | 1d | 2d | 3d | 4d | 5d | 6d | 7d |
|---|---|---|---|---|---|---|---|---|
| Connected Ret | 0.30*** | 0.32*** | 0.38*** | 0.41*** | 0.39** | 0.40 | 0.53** | 0.57** |
| | (7.60) | (5.31) | (3.89) | (3.98) | (2.72) | (1.87) | (2.79) | (2.84) |
| Constant | 0.0026* | 0.0044 | 0.010 | 0.013 | 0.017 | 0.025 | 0.030 | 0.043* |
| | (2.14) | (1.70) | (1.80) | (1.58) | (1.55) | (1.73) | (1.83) | (2.17) |
| Observations | 2623410 | 2578365 | 2506383 | 2443071 | 2386977 | 2335407 | 2287855 | 2244988 |

# Cross-Predictability

| *J* | *K*= | *12hr* | *1d* | *2d* | *3d* | *4d* | *5d* | *6d* | *7d* |
|---|---|---|---|---|---|---|---|---|---|
| *12hr* | | 0.0064 | 0.0052 | 0.0048 | 0.0029 | 0.0024 | 0.0027 | 0.0031 | 0.0028 |
| | | (3.53) | (3.36) | (3.92) | (2.92) | (2.74) | (3.06) | (3.58) | (3.16) |
| *1d* | | 0.0065 | 0.0071 | 0.0052 | 0.0036 | 0.0027 | 0.0030 | 0.0037 | 0.0031 |
| | | (3.31) | (3.68) | (3.25) | (2.67) | (2.34) | (2.59) | (3.30) | (2.87) |
| *2d* | | 0.0104 | 0.0075 | 0.0040 | 0.0033 | 0.0038 | 0.0045 | 0.0044 | 0.0034 |
| | | (4.80) | (3.58) | (1.97) | (1.82) | (2.30) | (2.88) | (3.20) | (2.46) |
| *3d* | | 0.0068 | 0.0046 | 0.0028 | 0.0029 | 0.0044 | 0.0045 | 0.0038 | 0.0026 |
| | | (3.16) | (2.11) | (1.23) | (1.40) | (2.30) | (2.49) | (2.31) | (1.59) |
| *4d* | | 0.0056 | 0.0049 | 0.0055 | 0.0062 | 0.0065 | 0.0059 | 0.0049 | 0.0040 |
| | | (2.55) | (2.19) | (2.36) | (2.69) | (2.93) | (2.76) | (2.43) | (1.97) |
| *5d* | | 0.0073 | 0.0072 | 0.0073 | 0.0073 | 0.0067 | 0.0056 | 0.0049 | 0.0038 |
| | | (3.03) | (2.77) | (2.71) | (2.80) | (2.73) | (2.45) | (2.20) | (1.71) |
| *6d* | | 0.0082 | 0.0080 | 0.0074 | 0.0062 | 0.0052 | 0.0047 | 0.0037 | 0.0029 |
| | | (3.22) | (2.90) | (2.57) | (2.29) | (2.02) | (1.88) | (1.59) | (1.32) |
| *7d* | | 0.0077 | 0.0074 | 0.0061 | 0.0044 | 0.0041 | 0.0036 | 0.0029 | 0.0025 |
| | | (3.08) | (2.68) | (2.18) | (1.69) | (1.60) | (1.45) | (1.25) | (1.16) |

# Takeaways:

**Connected currencies exhibit significantly higher comovement;**

- More than what all other characteristics can explain
- This effect increases in time-horizon
- Leads to cross-predictability

# Next:

**Are these results driven by unobservable characteristics that determine both returns and trading location?**

# Takeaways:

**Connected currencies exhibit significantly higher comovement;**

- More than what all other characteristics can explain
- This effect increases in time-horizon
- Leads to cross-predictability

# Next:

**Are these results driven by unobservable characteristics that determine both returns and trading location?**

# Evidence from a Quasi-Natural Experiment

- 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.
- The shock can be used to construct an instrument for changes in connectivity.

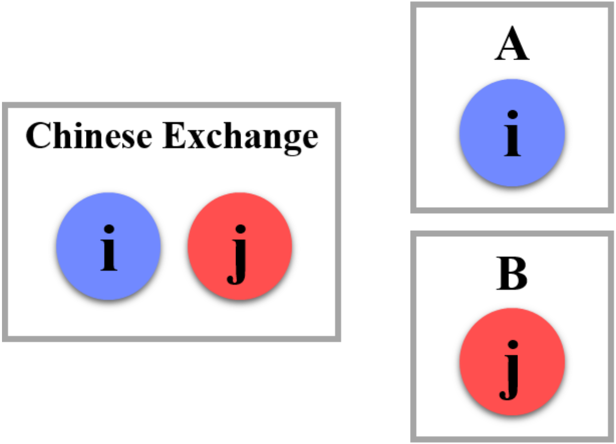
# Evidence from a Quasi-Natural Experiment

- 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.
- The shock can be used to construct an instrument for changes in connectivity.

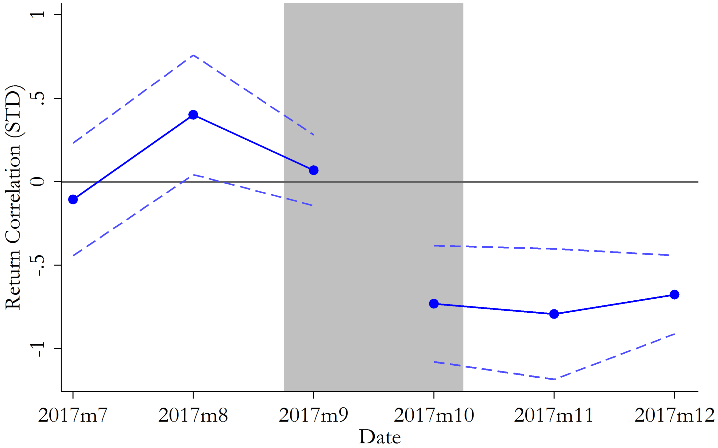
# Evidence from a Quasi-Natural Experiment

- 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.
- The shock can be used to construct an instrument for changes in connectivity.

# Example for Currencies Affected by the Shock



# Changes in Pairwise Correlations



# 2SLS Estimation

First stage:

$$\Delta Connectivity_{i,j} = \gamma_0 + \gamma_1 Connectivity_{i,j}^{Chinese} + \gamma^{Char} \Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Second stage:

$$\Delta Corr_{i,j} = \beta_0 + \beta_1 \Delta \widehat{Connectivity}_{i,j} + \beta^{Char} \Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Control group: Ten closest pairs based on the pairwise connectivity and the monthly trading volume of the two currencies in the month prior to shutdown.

# 2SLS Estimation

First stage:

$$\Delta Connectivity_{i,j} = \gamma_0 + \gamma_1 Connectivity_{i,j}^{Chinese} + \gamma^{Char} \Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Second stage:

$$\Delta Corr_{i,j} = \beta_0 + \beta_1 \Delta \widehat{Connectivity}_{i,j} + \beta^{Char} \Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Control group: Ten closest pairs based on the pairwise connectivity and the monthly trading volume of the two currencies in the month prior to shutdown.

# 2SLS Estimation

First stage:

$$\Delta Connectivity_{i,j} = \gamma_0 + \gamma_1 Connectivity_{i,j}^{Chinese} + \gamma^{Char}\Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Second stage:

$$\Delta Corr_{i,j} = \beta_0 + \beta_1 \Delta \widehat{Connectivity}_{i,j} + \beta^{Char}\Delta Similarity_{i,j}^{Char} + \delta_c + \varepsilon_{i,j}$$

Control group: Ten closest pairs based on the pairwise connectivity and the monthly trading volume of the two currencies in the month prior to shutdown.

# Instrumental Variables 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 |

# New Exchange Listings and Changes in Comovement

Difference-in-Differences Estimation:

$$Corr_{i,j,t} = \beta_0 + \beta_1 Treated_{i,j} + \sum_{t=-1}^{3} \gamma_t Treated_{i,j} * M_t + \beta^{Char} Similarity^{Char}_{i,j,t-1} + \sum_{t=-1}^{3} \gamma_t^{Char} Similarity^{Char}_{i,j,t-1} * M_t + \delta_{c,t} + \delta_{i,j} + \varepsilon_{i,j,t}$$

Control group: Ten closest pairs based on connectivity and trading volume of the two currencies in the month prior to listing.

# New Exchange Listings and Changes in Comovement

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treated | -0.058 | -0.049 | -0.050 | -0.049 |
| | (-1.35) | (-1.13) | (-1.15) | (-1.14) |
| Treated*M=-1 | 0.026 | 0.017 | 0.019 | 0.018 |
| | (0.58) | (0.37) | (0.42) | (0.39) |
| Treated*M=0 | 0.008 | -0.000 | 0.007 | 0.010 |
| | (0.17) | (-0.01) | (0.16) | (0.22) |
| Treated*M=1 | $0.142^{*}$ | $0.135^{*}$ | $0.129^{*}$ | $0.126^{*}$ |
| | (2.46) | (2.28) | (2.18) | (2.12) |
| Treated*M=2 | $0.192^{*}$ | $0.185^{*}$ | $0.184^{*}$ | $0.183^{*}$ |
| | (2.54) | (2.42) | (2.36) | (2.35) |
| Treated*M=3 | $0.301^{***}$ | $0.294^{***}$ | $0.294^{***}$ | $0.294^{***}$ |
| | (3.42) | (3.37) | (3.33) | (3.33) |
| $\text{Similarity}^{\text{Volume}}$ | | -0.008 | -0.021 | -0.020 |
| | | (-0.56) | (-1.39) | (-1.33) |
| $\text{Similarity}^{\text{SameNExch}}$ | | -0.001 | -0.001 | -0.003 |
| | | (-0.02) | (-0.02) | (-0.11) |
| Cohort-Time FE | Yes | Yes | Yes | Yes |
| Pair FE | Yes | Yes | Yes | Yes |
| Observations | 225011 | 224466 | 224466 | 224466 |
| Dyadic Clustering | Yes | Yes | Yes | Yes |
| $\text{Similarity}^{\text{Volume}}*\text{M}$ | No | No | Yes | Yes |
| $\text{Similarity}^{\text{SameNExch}}*\text{M}$ | No | No | No | Yes |

# Takeaways:

- **Connected currencies exhibit significantly higher comovement.**
- **Exogenous changes in connectivity cause changes in the comovement.**

# Next:

- **Does the network effect play an important role in explaining the results?**

# Takeaways:

- **Connected currencies exhibit significantly higher comovement.**
- **Exogenous changes in connectivity cause changes in the comovement.**

# Next:

- **Does the network effect play an important role in explaining the results?**

# Amplifying Effect of Network Externalities

Hypothesis:

Network externalities should amplify the effect of common demand shocks on comovement.

Empirical Strategy:

Exploiting cross-sectional variation in importance of the network effect for different cryptocurrencies.

# Amplifying Effect of Network Externalities

Hypothesis:

Network externalities should amplify the effect of common demand shocks on comovement.

Empirical Strategy:

Exploiting cross-sectional variation in importance of the network effect for different cryptocurrencies.

# Capturing Cross-Sectional Variation in the Network Effect

- Quantifying the extent that investors and community of different cryptocurrencies "believe" the currency's underlying value is derived from the network effect.

- Using 12 million currency-specific comments on Reddit to capture this variation:
  1. Reading and labeling 10,000 comments as a training sample.
  2. Using random forest to extract important features that distinguishes the comments.
  3. Feeding the rest of 12M comments into the model for labeling.
  4. Quantifying the percentage of comments that are labeled *1* for each cryptocurrency.

# Capturing Cross-Sectional Variation in the Network Effect

- Quantifying the extent that investors and community of different cryptocurrencies "believe" the currency's underlying value is derived from the network effect.

- Using 12 million currency-specific comments on Reddit to capture this variation:
  1. Reading and labeling 10,000 comments as a training sample.
  2. Using random forest to extract important features that distinguishes the comments.
  3. Feeding the rest of 12M comments into the model for labeling.
  4. Quantifying the percentage of comments that are labeled *1* 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.”
- “I think the point is network effect. The bubbles bring in more userbase thus increasing network effect.”
- “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.”

# 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."
- "I think the point is network effect. The bubbles bring in more userbase thus increasing network effect."
- "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."

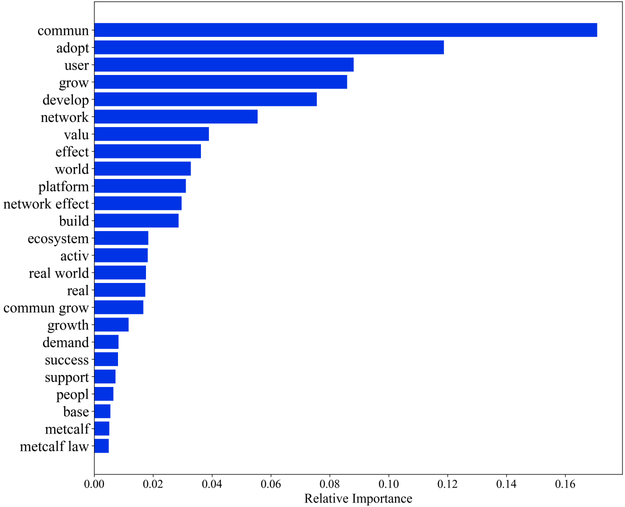
# Examples of Comments

- "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."
- "I think the point is network effect. The bubbles bring in more userbase thus increasing network effect."
- "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."

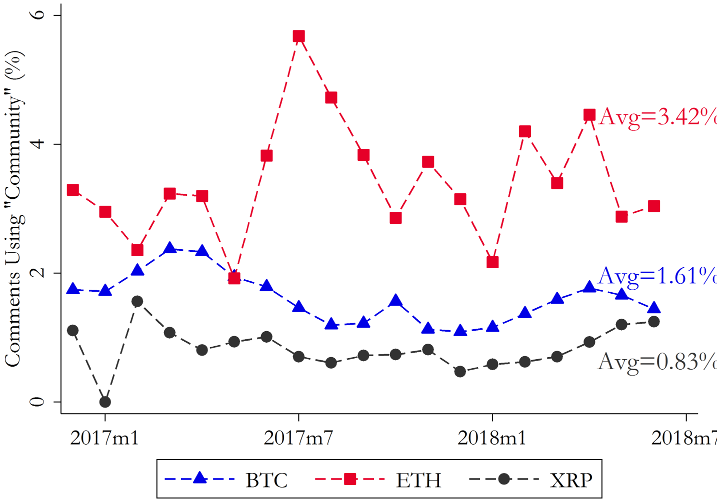
# Examples of Comments

- “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.”
- “I think the point is network effect. The bubbles bring in more userbase thus increasing network effect.”
- “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



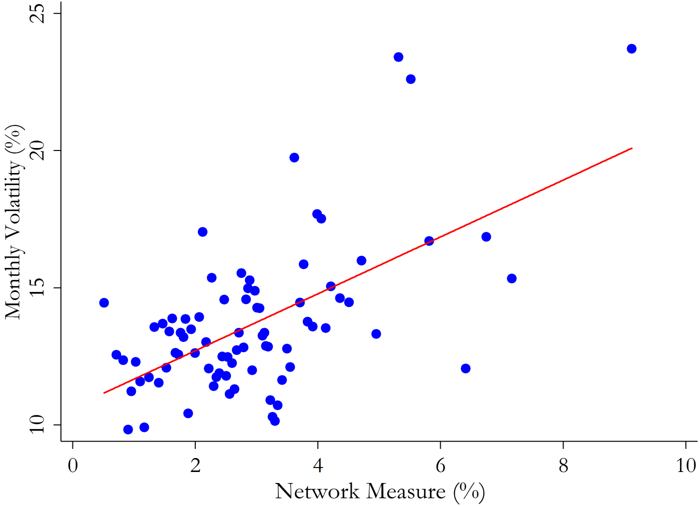
# The Network Measure for Top Currencies



# The Network Measure for Top Currencies

| N | Ticker | Perc_Comm | PlatToken |
|---|---|---|---|
| 1 | ETH | 3.4 | 1 |
| 2 | ADA | 2.5 | 1 |
| 3 | IOTA | 2.3 | 0 |
| 4 | EOS | 2.2 | 1 |
| 5 | BTC | 1.6 | 0 |
| 6 | BCH | 1.6 | 0 |
| 7 | TRX | 1.5 | 0 |
| 8 | XLM | 1.5 | 0 |
| 9 | LTC | 1.3 | 0 |
| 10 | XRP | 0.8 | 0 |

# Binscatter of the Network Measure and Volatility



# Amplifying Effect of Network Externalities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Connectivity | 0.151*** | 0.137*** | 0.138*** | 0.139*** |
| | (10.75) | (9.53) | (7.87) | (7.99) |
| Hi_Commun | 0.184*** | 0.176*** | 0.177*** | 0.157** |
| | (3.94) | (3.78) | (3.79) | (3.16) |
| Connectivity*Hi_Commun | 0.066** | 0.070*** | 0.070*** | 0.075** |
| | (3.29) | (3.47) | (3.49) | (3.17) |
| $\text{Similarity}^{\text{Volume}}$ | | 0.074*** | 0.074*** | 0.075*** |
| | | (4.58) | (4.61) | (3.73) |
| $\text{Similarity}^{\text{CoinToken}}$ | | 0.022 | | |
| | | (1.83) | | |
| $\text{Connectivity*Similarity}^{\text{Volume}}$ | | | 0.000 | |
| | | | (0.03) | |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 80940 | 80940 | 80940 | 40123 |
| Adjusted $R^2$ | 0.229 | 0.230 | 0.230 | 0.230 |
| Dyadic Clustering | Yes | Yes | Yes | Yes |

# Conclusion

This paper documents a strong comovement structure in cryptocurrency returns and the amplifying effect of network externalities.

1. **Cryptocurrencies that have similar investor bases comove substantially more than currencies with different investors.**
    a) Cryptocurrencies with one standard deviation higher “connectivity” exhibit approximately 0.2 standard deviations higher correlations.
    b) This effect cannot be explained by similarities in technological features or other characteristics.
    c) Exogenous changes in the investor base cause significant changes in comovement.
    d) The effect increases in time-horizon and leads to a strong cross-predictability.
2. **The network effect plays an important role in explaining the magnitude of the results.**