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Trading and Arbitrage in Cryptocurrency Markets

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Motivation

- The spectacular rise and fall in value of cryptocurrencies attracted a lot of public attention
- Cryptocurrenciesare built on the blockchain technology that allows verification of payments in the absence of a centralized custodian
- Bitcoin was originally introduced in a paper by Nakamoto (2008) and came into existence in 2009
- At the peak, more than 25 actively traded cryptocurrencies with the aggregate market cap of $500B and more than 15 million of active investors

This paper

- A systematic analysis of the trading and efficiency of crypto markets
- Several features make the cryptocurrency market a unique laboratory for studying arbitrage and price formation:
    - Many non-integrated exchanges that are independently owned and exist in parallel across countries
    - Many 'naive' investors and few large sophisticated investors (e.g., DRW, Jump Trading, or Hehmeyer Trading)
    - Blockchain technology alleviates some constraints (e.g., capital mobility) but introduces others (the transfer of value between exchanges is subject to a delay)

  ⇒ Markets can potentially be segmented

⇒ Looking across markets can help us understand which frictions lead to market segmentation and can give us a more complete picture of investors' demand for cryptocurrencies

Main results

- History of bitcoin exchanges marked by recurring episodes of arbitrage opportunities opening and closing again
  - The total size of arbitrage profits from December 2017 to February 2018 is well above $1 billion
  - Arbitrage opportunities persist for several hours or even days and weeks
- Arbitrage opportunities are larger *across* countries (or regions) than *within* the same country
- Arbitrage spreads across countries show strong co-movement
  - Price deviations are asymmetric: Bitcoin price in rest of world is above US and Europe
  - Countries with higher average Bitcoin premium also respond more strongly to periods of ’buying pressure’
- Arbitrage spreads are much smaller for exchange rates between different cryptocurrencies compared to exchange rates between cryptocurrencies and fiat currencies

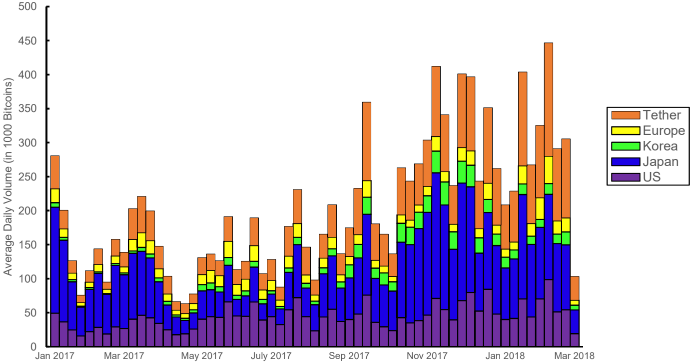
Main results (cont.)

- Bitcoin returns and arbitrage spreads vary with net order flows
- We decompose signed volume on each exchange into a common component and an idiosyncratic, exchange-specific component
  - The common component explains 80 percent of the variation in Bitcoin returns
  - Buying 10,000 Bitcoins raises returns by 4% at the daily frequency
  - The idiosyncratic components of order flow play an important role in explaining the size of the arbitrage spreads between exchanges

Data

- Tick level trading data from Kaiko, a private firm that has been collecting trading information about crypto currencies since 2014
- The Kaiko data cover the 17 largest and most liquid exchanges: Binance, Bitfinex, bitFlyer, Bithumb, Bitstamp, Bitbox, Bittrex, BTCC, BTC-e, Coinbase, Gemini, Huobi, Kraken, OkCoin, Poloniex, Quoine, and Zaif
- The 17 exchanges account for 85% of total Bitcoin volume to fiat currencies
- Expanded sample of 34 exchanges across 19 countries from additional sources such as bitcoincharts.com and individual exchanges themselves

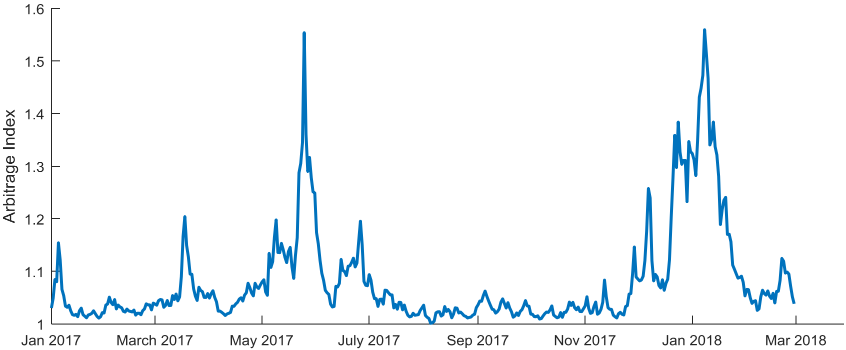
Summary statistics: volume



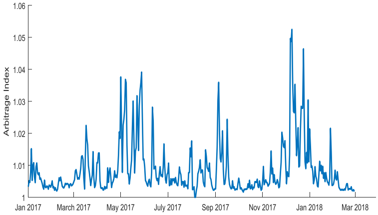
Summary statistics: returns

Return frequency	Std. Dev	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	cross correlation
5 - Minute	1.40	1.56	365.64	0.07	-0.01	0.01	0.57
Hour	1.22	-0.06	13.86	-0.07	-0.05	-0.01	0.83
Daily	1.07	0.29	3.85	-0.01	0	0.02	0.95

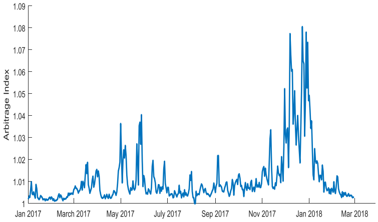
Arbitrage index (all exchanges)



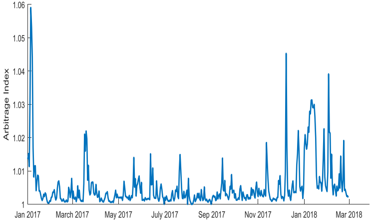
Arbitrage index (within regions)



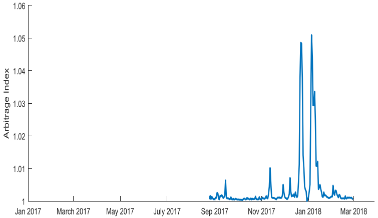
US



Europe

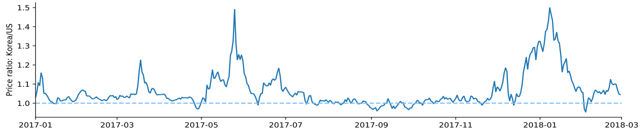


Japan

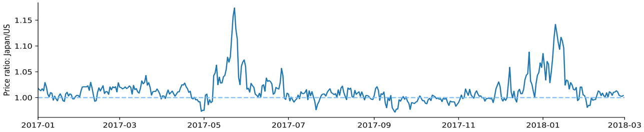


Korea

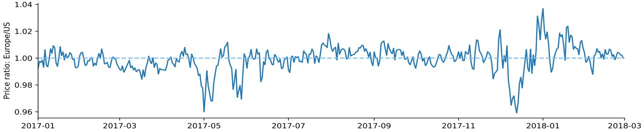
Arbitrage index (between regions)



Panel A: US vs. Korea

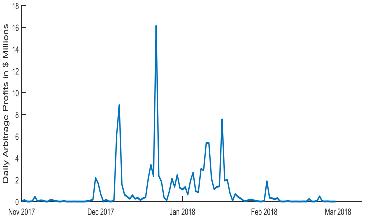


Panel B: US vs. Japan

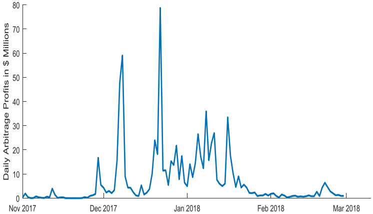


Panel C: US vs. Europe

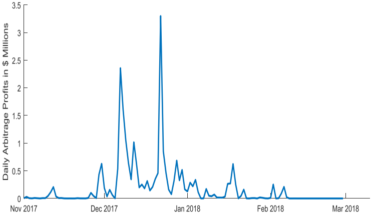
Arbitrage profit (between regions)



Japan: total profit $250M



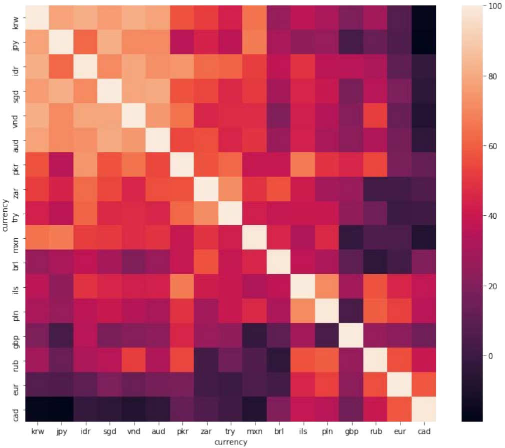
Korea: total profit $1B



Europe: total profit $25M

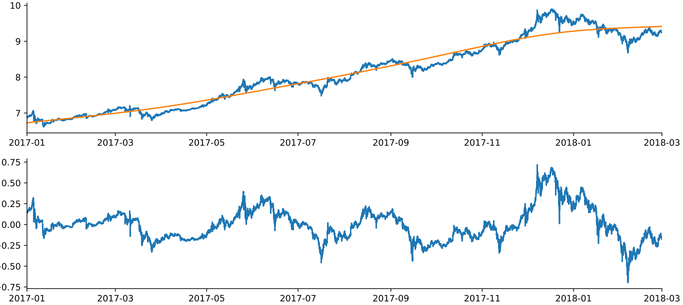
Co-Movement of arbitrage spreads

- Correlation matrix: Arbitrage spreads across regions



Buying pressure

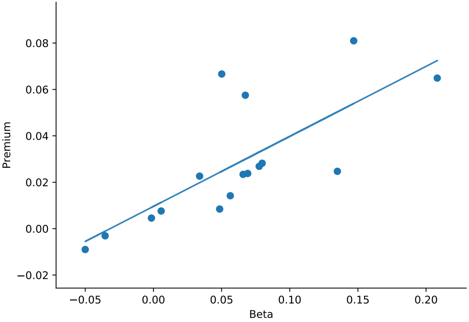
- Use standard Hodrick-Prescott filter to calculate the smoothed Bitcoin price at the weekly level in the US
- Calculate deviations of the actual log price from the smoothed log price to provide metric of "buying pressure" in the US



Arbitrage premium and buying pressure

- Regress arbitrage spreads of individual countries relative to US price on our measure of buying pressure
  - A strong positive Bitcoin beta: Countries outside the US and Europe respond strongly to price pressure in the US

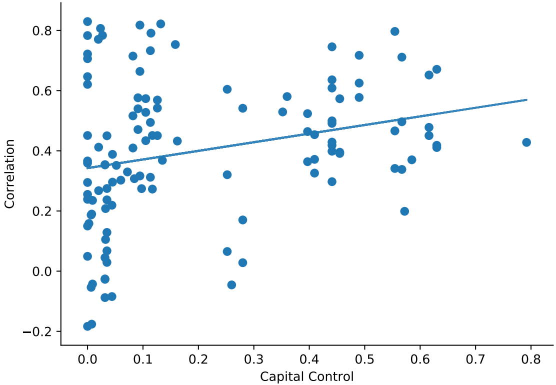
- Countries that have a higher average Bitcoin premium over the US, also show larger Bitcoin beta



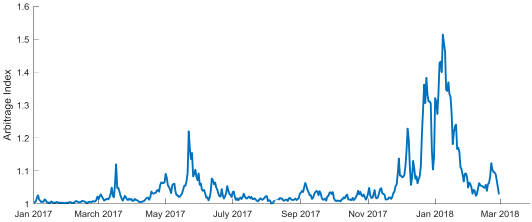
The Role of Capital Controls

- Regression of pairwise correlation between arbitrage spreads on pairwise measure of capital control based on Fernandez et al (2015):

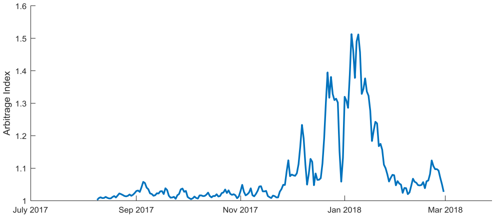
$$CapContr_{ij} = \gamma_i \gamma_j \tag{1}$$



Arbitrage index: Ethereum and Ripple

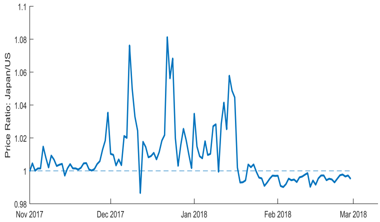


ethereum



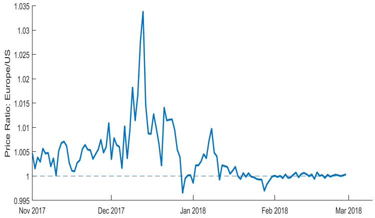
ripple

Ethereum-Bitcoin rate between regions



Japan

Korea



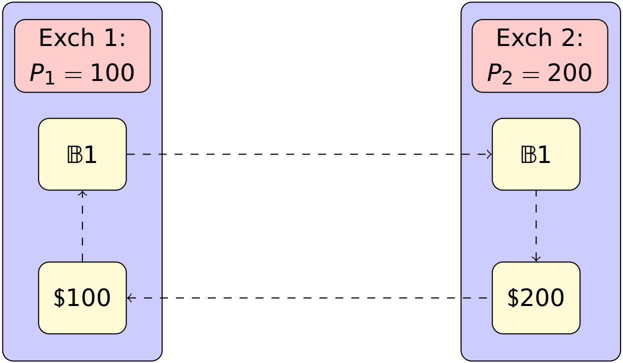
Europe

How to interpret the findings?

- The marginal investor outside the US and Europe is willing to pay more for Bitcoin in response to positive news. Possibly because the value of cryptocurrencies is higher in countries with less developed financial markets/ poorer investment opportunities for retail investors
- To observe sustained price deviations markets must be segmented

Implementation of arbitrage

- In a frictionless world if prices are different across exchanges there is a riskless arbitrage:



- Transactions take time $\Rightarrow$ need to buy and sell bitcoin simultaneously

Implementation of arbitrage II

- Ideally, an arbitrageur would like to short sell Bitcoin on the market where the price is high ⇒ often not feasible, because many exchanges do not allow short-sales
- Two solutions:
  - Trading on margin ⇒ similar to short-sales, but does not allow for physical settlement ⇒ convergence risk
  - Hold a positive balance of Bitcoin on both exchanges and simultaneously buy and sell Bitcoins across the two exchanges whenever the price on one exchange deviates from that on the other ⇒ price risk
- To mitigate the price risk the arbitrageur can
  - Short-sale Bitcoins
  - Borrow Bitcoin from people who hold big amounts of Bitcoin without an interest to sell (hodlers)
  - Use futures contracts (from December 2017)

Frictions I: Transaction costs

- Buying and selling Bitcoins on an exchange: bid-ask spread (1-10bp), exchange fees (0-10bp)
- Sending Bitcoins across exchanges via Bitcoin protocol (very small for large transactions)
- Exchange deposit/withdrawal fees (vary, small for large transactions)
- For large players the round-up trading costs should be within 50 to 75 bp — very low compared to the arbitrage spreads

Frictions II: Exchange governance risk

- To trade on an exchange the arbitrageur has to give up control of her coins to the exchange ⇒ if the exchange is hacked (and many were) the arbitrageur can loose her funds
- Not a compelling explanation:
  - Arbitrage spreads are much larger across than within regions ⇒ for exchange risk to explain this pattern the exchange risk must be region specific
  - Concerns about the governance risk of an exchange should affect its volume and possibly bid-ask spreads
  - There is significant heterogeneity in the liquidity of exchanges within a region but nevertheless arbitrage spreads are small between them
  - Arbitrage spreads have common component

Frictions III: Capital controls

- The arbitrageur has to able to trade across multiple exchanges and transfer capital between them
    - Many retail investors face restrictions on which exchanges they can trade. Not binding for large institutions
    - Capital controls for fiat currencies (e.g. Korea, binding for retail investors, for large financial institutions - unclear)
    - Arbitrage is much smaller for cryptocurrency pairs $\Rightarrow$ sign that capital controls contribute to the limits of arbitrage
    - In the presence of capital controls the arbitrageur can still bet on the price convergence across the two regions. But capital controls reduce the efficiency of arbitrage capital

Conclusion

- Document persistence of large arbitrage spreads in the price of cryptocurrencies to fiat currencies across exchanges
  - Not driven by transaction costs or differential governance risk across exchanges
  - Linked to capital controls across regions (effects are much smaller for exchange rates between cryptocurrencies)
- Arbitrage spreads are correlated across regions and time
- Countries with tighter capital controls and worse financial markets show higher arbitrage spreads

Thank You!

Appendix: Net order flow and prices

- There is a strong positive relationship between net order flows and prices in "traditional" financial markets
  - Currency markets: Evans and Lyons (2002)
  - Bond markets: Brandt and Kavajecz (2004)
  - S&P 500 futures market: Deuskar and Johnson (2011)
  - US stock market: Hendershott and Menkveld (2014)
- Usually attributed to price discovery. It is less clear what the fundamentals are in the case of cryptocurrency markets and whether there are any traders who have more information than others

Net order flow and prices (cont.)

- A common way to estimate the impact of net order flow is to regress returns on the signed volume
- The complication in the bitcoin market is that the same asset is traded simultaneously on multiple exchanges and often at different prices
  - Therefore, when forming their demand investors might not only look at prices on their own exchange but also take into account prices on the other exchanges where bitcoin is traded
  - Hence, a regression of returns on signed volume in each market separately may give a biased picture of the true impact of net order flow

Model: signed volume

$$s_{it} = \bar{s}_i + \beta_i^s s_t^* + \hat{s}_{it}, \quad \sum \beta_i^s = 1 \tag{2}$$

- s_{it} is signed volume on exchange i
- s_t^* is the common component for all exchanges
- $\hat{s}_{it}$ is an exchange specific component

$$E[s_t^*] = 0, \quad E[\hat{s}_{it}] = 0$$
$$E[s_t^* \hat{s}_{it}] = 0, \quad E[\hat{s}_{it}\hat{s}_{jt}] = 0, \quad \text{for} \quad i \neq j$$

- Linear model:

$$s_t^* = \sum w_i^s s_{it}, \quad \sum \beta_i^s w_i^s = 1$$

Model: returns

$$r_{it} = \bar{r}_i + \beta_i^r s_t^* + \hat{r}_{it} \qquad (3)$$

- r_{it} is log-return on exchange i
- r_t^* is the common component for all exchanges
- $\hat{r}_{it}$ is an exchange specific log-return

$$E[r_t^*] = 0, \quad E[\hat{r}_{it}] = 0$$

$$E[r_t^* \hat{r}_{it}] = 0, \quad E[\hat{r}_{it}\hat{r}_{jt}] = 0, \quad \text{for} \quad i \neq j$$

- Linear model:

$$r_t^* = \sum w_i^r r_{it}, \quad \sum w_i^r = 1$$

Estimation: signed volume

	Bitfinex	Coinbase USD	Bitstamp USD	Gemini	Kraken USD	Kraken EUR	Coinbase EUR	Bitstamp EUR	bitFlyer	Quoine	Zaif	Bithumb	Poloniex	Bittrex
5-min frequency														
β_i^S	0.35	0.12	0.10	0.04	0.03	0.05	0.02	0.02	0.09	0.041	0.03	0.03	0.03	0.03
w_i^S	0.44	1.17	1.19	0.70	1.54	1.14	4.72	1.90	0.95	0.28	1.96	1.84	1.71	1.93
R^2	0.60	0.58	0.53	0.21	0.31	0.33	0.45	0.20	0.42	0.08	0.30	0.25	0.33	0.35
hourly frequency														
β_i^S	0.32	0.13	0.10	0.05	0.045	0.06	0.02	0.02	0.08	0.03	0.03	0.03	0.04	0.04
w_i^S	0.42	0.80	1.21	0.82	2.53	1.58	3.97	1.68	0.68	0.10	1.47	0.86	1.80	1.73
R^2	0.67	0.61	0.65	0.35	0.62	0.59	0.56	0.28	0.42	0.03	0.38	0.29	0.50	0.46
daily frequency														
β_i^S	0.31	0.12	0.11	0.05	0.05	0.07	0.01	0.02	0.07	0.02	0.03	0.04	0.04	0.04
w_i^S	0.37	0.32	1.26	1.49	3.26	1.70	1.79	1.67	0.37	0.05	1.71	0.52	2.20	1.99
R^2	0.67	0.39	0.70	0.56	0.76	0.67	0.29	0.33	0.30	0.01	0.47	0.26	0.61	0.58

Estimation: returns

	Bitfinex	Coinbase USD	Bitstamp USD	Gemini	Kraken USD	Kraken EUR	Coinbase EUR	Bitstamp EUR	bitFlyer	Quoine	Zaif	Bithumb	Poloniex	Bittrex
5-min frequency														
β_i^r	1.12	1.02	1.03	1.03	0.70	0.70	0.93	0.97	0.84	0.92	0.82	0.82	1.07	1.06
w_i^r	0.16	0.11	0.12	0.16	0.03	0.03	0.04	0.05	0.05	0.02	0.02	0.03	0.10	0.05
R^2	0.89	0.82	0.83	0.88	0.44	0.43	0.61	0.64	0.61	0.44	0.38	0.49	0.80	0.68
hourly frequency														
β_i^r	1.03	0.99	1.00	1.00	0.96	0.96	0.97	0.99	0.89	0.95	0.91	0.85	1.04	1.08
w_i^r	0.14	0.12	0.14	0.15	0.06	0.04	0.03	0.08	0.02	0.02	0.02	0.02	0.10	0.06
R^2	0.96	0.95	0.96	0.97	0.91	0.87	0.83	0.93	0.75	0.77	0.71	0.66	0.95	0.92
daily frequency														
β_i^r	1.03	0.98	1.00	1.00	0.97	0.98	0.95	0.98	1.10	1.11	1.12	0.98	1.02	1.02
w_i^r	0.08	0.05	0.31	0.15	0.07	0.04	0.02	0.10	0.01	0.01	0.01	0.01	0.07	0.06
R^2	0.99	0.98	0.99	0.99	0.99	0.98	0.95	0.99	0.89	0.90	0.89	0.80	0.99	0.98

Sytematic price impact

$$r_t^* = \lambda s_t^* + \sum_{\tau=1}^{T} \lambda_\tau s_{\tau-1}^* + \varepsilon_t$$

	5-min frequency $\lambda \times 10^4 (\%)$			hourly frequency $\lambda \times 10^4 (\%)$			daily frequency $\lambda \times 10^4 (\%)$		
s_t^*	8.8	9.9	10.1	6.0	6.6	6.6	3.6	3.9	4.0
	(80.06)	(86.19)	(88.05)	(35.12)	(39.7)	(40.41)	(16.92)	(19.93)	(18.96)
s_{t-1}^*		-3.1	-2.6		-2.1	-2.0		-1.1	-1.1
		(-36.54)	(-32.24)		(-16.53)	(-15.67)		(-4.05)	(-3.62)
s_{t-2}^*			-0.8			-0.4			-0.0
			(-11.68)			(-3.71)			(-0.2)
s_{t-3}^*			-0.5			-0.1			-0.1
			(-7.56)			(-1.22)			(-0.76)
s_{t-4}^*			-0.4			-0.3			-0.3
			(-6.88)			(-3.00)			(-1.71)
s_{t-5}^*			-0.3			-0.1			0.3
			(-5.24)			(-1.33)			(1.57)
R^2	0.54	0.60	0.61	0.6	0.66	0.67	0.69	0.75	0.76

Exchange-specific price impact

$$p_{it} = p_t^* + \hat{p}_{it},$$
$$\hat{p}_{it} = \lambda_i \hat{s}_{it} + \sum_{s=1}^{3} a_{i,s}\hat{p}_{it-s} + \varepsilon_{it}$$

	Bitfinex	Coinbase USD	Bitstamp USD	Gemini	Kraken USD	Kraken EUR	Coinbase EUR	Bitstamp EUR	bitFlyer	Quoine	Zaif	Bithumb	Poloniex	Bittrex
							5-min frequency							
$\lambda_i \times 10^4(\%)$	2.86	17.35	5.76	8.37	40.95	41.66	172.03	15.8	17.13	4.35	59.61	32.1	20.1	22.66
	(16.49)	(22.83)	(9.18)	(14.35)	(21.14)	(27.66)	(25.64)	(7.43)	(22.26)	(6.58)	(13.34)	(25.13)	(12.28)	(14.00)
a_{1i}	0.6	0.63	0.55	0.59	0.56	0.63	0.73	0.5	0.83	0.79	0.84	0.83	0.61	0.6
	(48.44)	(16.28)	(56.57)	(34.58)	(43.48)	(40.07)	(29.02)	(25.25)	(40.69)	(26.36)	(14.73)	(50.95)	(54.99)	(61.34)
a_{2i}	0.23	0.18	0.23	0.24	0.2	0.19	0.16	0.26	0.12	0.15	0.01	0.12	0.21	0.21
	(17.07)	(5.58)	(21.47)	(13.5)	(14.75)	(11.51)	(4.18)	(18.78)	(4.8)	(5.55)	(0.08)	(6.45)	(19.32)	(21.32)
a_{3i}	0.16	0.18	0.2	0.16	0.21	0.16	0.1	0.23	0.04	0.05	0.15	0.05	0.17	0.18
	(12.84)	(5.51)	(21.89)	(11.18)	(19.68)	(9.62)	(4.1)	(13.54)	(1.79)	(2.59)	(3.3)	(3.64)	(16.56)	(18.78)
R-square	0.98	0.97	0.94	0.96	0.89	0.95	0.98	0.95	0.99	0.98	0.98	0.99	0.99	0.98