2025 ABFER

Are Arbitrageurs Less Affected by Behavioral Biases? Evidence from the Cryptocurrency Market

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Motivation:

Arbitrage and The Limits to Arbitrage

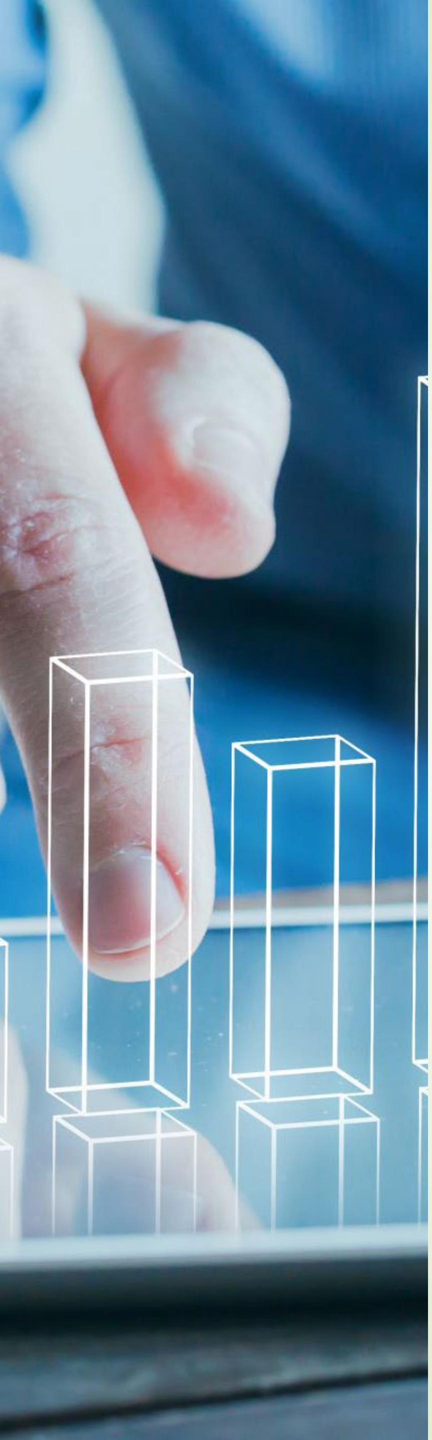
- Arbitrage is at the heart of modern finance
  - A large part of asset pricing studies builds on the **Arbitrage Pricing Theory (APT)**. (Ross, 1976)
  - Market efficiency depends on the **frictions** faced by arbitrageurs
- The limits of arbitrage:
  - Arbitrageurs are **rational**.
  - But they face **noise trader risk** (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010).
- **Our Question:** could arbitrageurs themselves be subject to behavioral biases?
  - If so, it implies a **novel** type of **limits of arbitrage**, which might have important implications.

Motivation:
Can arbitrageurs be behavioral biased?

- The literature lacks direct evidence:
  - Sophisticated investors, like **mutual fund managers**, are subject to various behavioral biases (e.g., Frazzini, 2006; Cici, 2012; Daniel et al., 1998; Baker et al., 2010; Coval and Moskowitz, 1999; Kacperczyk et al., 2016),
  - However, biased fund managers typically underperform the market and thus less qualified as arbitrageurs
- Our paper aims to fill the gap:
  - The cryptocurrency market helps identify arbitrage opportunities and hence arbitrageurs.
  - We use **account-level** data in from a major Indian crypto exchange and report striking observations.

Our main results

- We use triangular arbitrage opportunities to identify arbitrageurs.
  - **Arbitrage scores:** the trading alignments with arbitrage.
  - **Bias scores** are based on extrapolation (DOX), the disposition effect (DE), lottery preference (LP), and overtrade (Turnover)
- Investors with **higher arbitrage (bias) scores** can generate **better (worse) performance**.
- (Surprising finding) Arbitrageurs exhibit a **higher** level of bias. Behavioral biases are also **more harmful** to **arbitrageurs' performance.**
- Market efficiency is greatly affected:
  - **Arbitrageurs** conduct informed trading
  - Their behavioral biases **undermine** informed trading, indicating a big impact of **arbitrageurs' biases** on market efficiency.



Roadmap

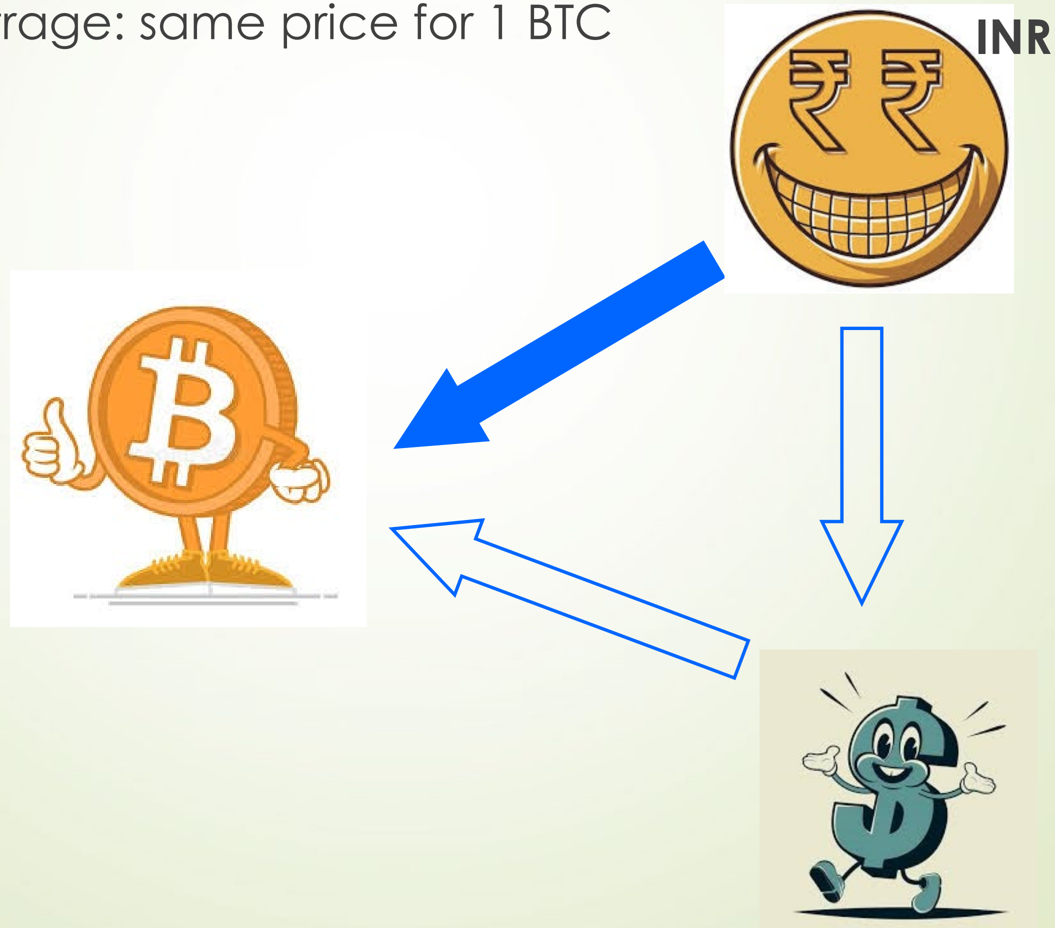
- Data sample and Arbitrage scores
- Performance tests
- Market efficiency implications
- Additional Analysis: trading costs, persistence, and experience

1.1 Data and Sample

- Trading data from a major Indian crypto exchange
  - **Account-level** trading records
  - Local daily token prices
  - **605,848 valid traders, 42,617,842 trades**;
  - Top 30 tokens in the exchange (represents 88% of sample trading volume)
- CoinMarketCap data
  - Daily token USD price index
  - Daily token market cap in USD
- Bloomberg data
  - USD/INR exchange rate
- Testing period: March 2018 – March 2022 (weekly)

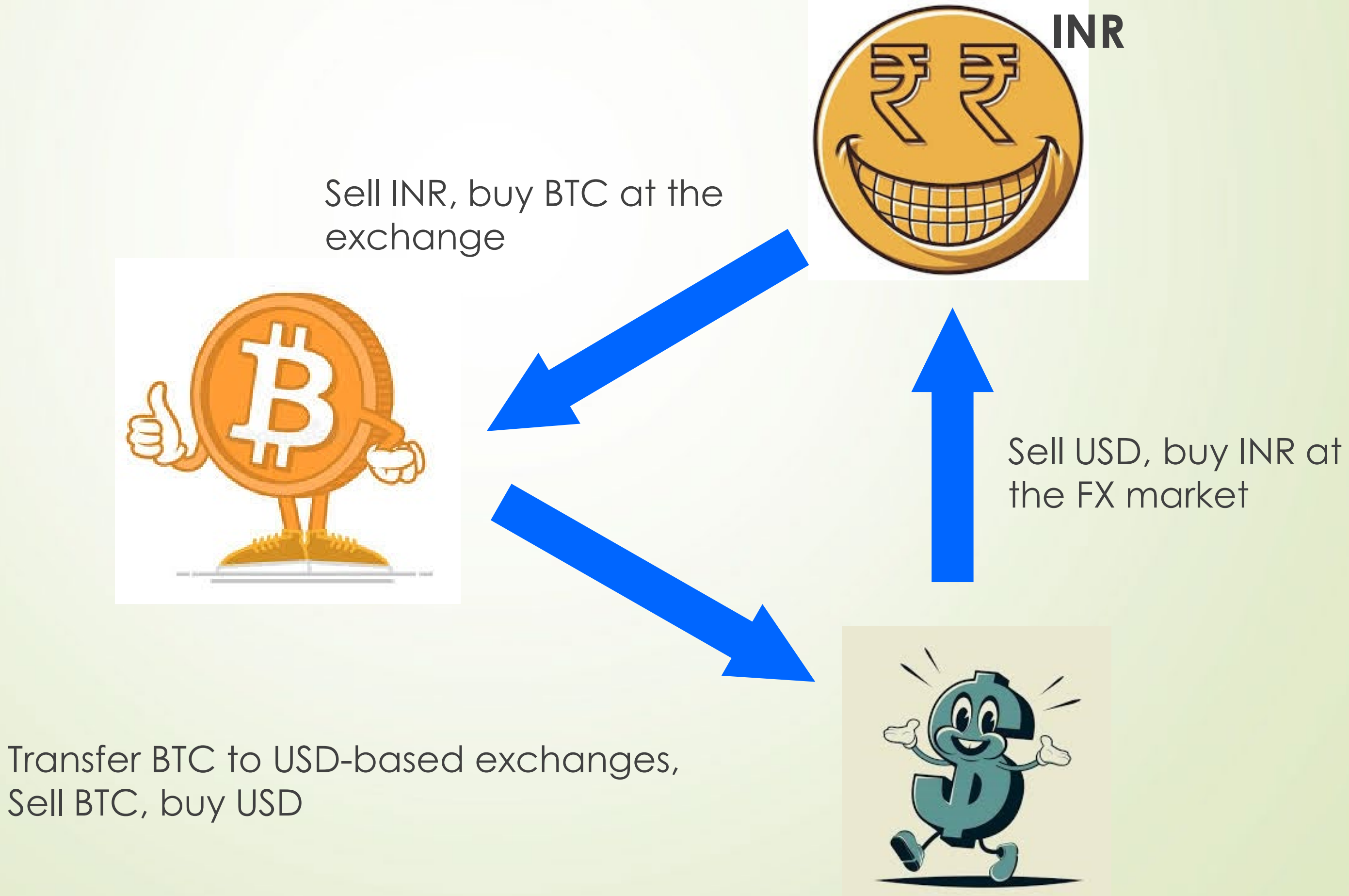
1.2 Triangular arbitrage
The BTC-USD-INR example

- Suppose an Indian investor wants to buy Bitcoin (BTC)
  - Direct: Indian Rupee (INR) ➔ BTC
  - Indirect: INR ➔ USD ➔ BTC.
- No arbitrage: same price for 1 BTC



1.2 Triangular arbitrage
The BTC-USD-INR example

- What if prices are different? (as vast studies suggest)
- **Triangular arbitrage**
  - E.g., if BTC is cheaper in India than in the United States



1.3 How to quantify triangular arbitrage opportunities?

- The arbitrage index:

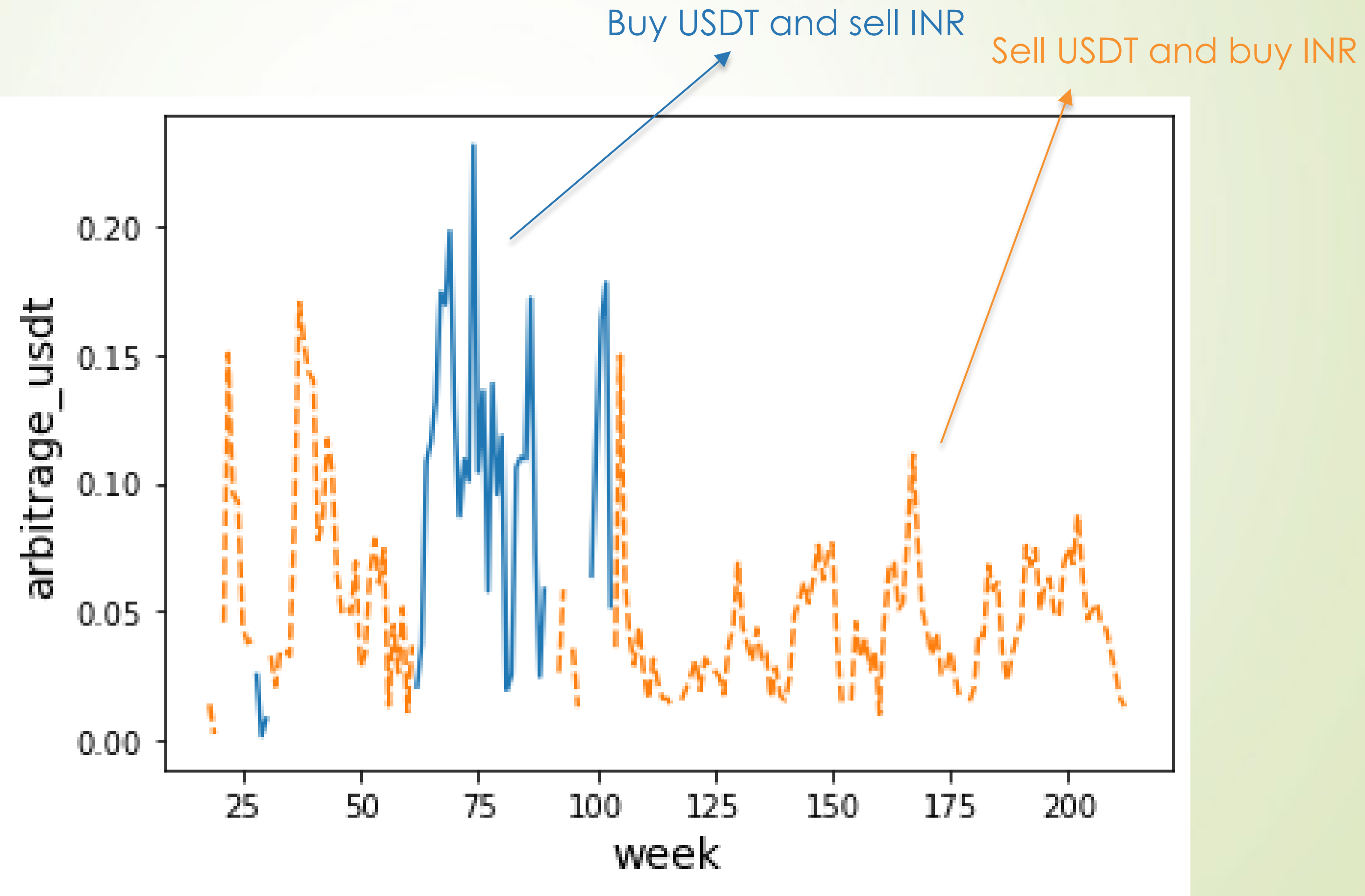
$$\Delta_t = \frac{\frac{BTC/USD}{BTC/INR} - INR/USD}{INR/USD}$$

INR/USD = Daily exchange rate on FX market (Bloomberg)
BTC/USD = Quoted price of BTC on USD (CoinMarketCap)
BTC/INR = Quoted price of BTC on INR (Crypto exchange)

- $\Delta_t = 0$: No arbitrage.
- When $\Delta_t > 0$, BTC is cheaper in India than in the United States. (Arbitragers could gain by INR ➔ BTC ➔ USD ➔ INR)

1.3 The arbitrage index in practice
The USDT-USD-INR example

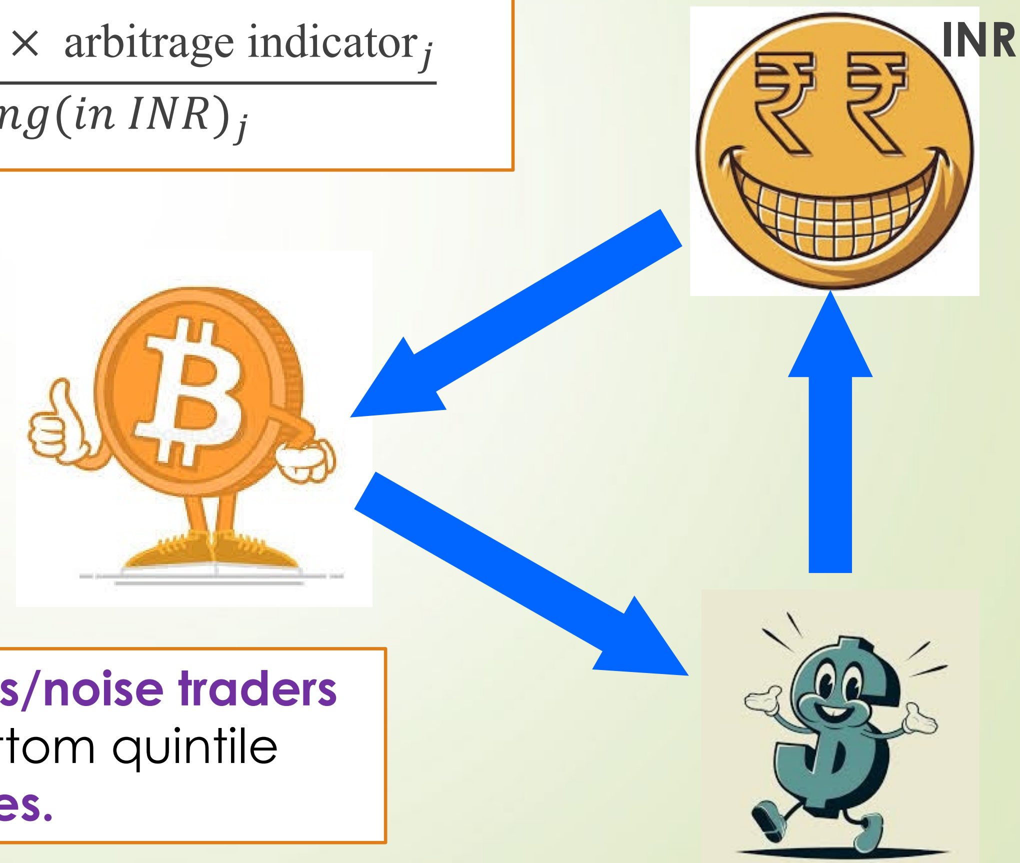
- Triangular arbitrage opportunities are prevalent. Below is an example of USDT (weekly plot, 0.2 = 20% return).



1.4 From Arbitrage Index to Arbitrage score

For trader i at week t, The arbitrage score (AS) is defined as the total trading volume aligned with arbitrage direction, scaled by the period-end portfolio holding

$$AS_{i,t} = \frac{\sum_{j,t} trade\ volume\ (in\ INR)_j\ \times\ \text{arbitrage indicator}_j}{\sum_{j,t} portfolio\ holding(in\ INR)_j}$$



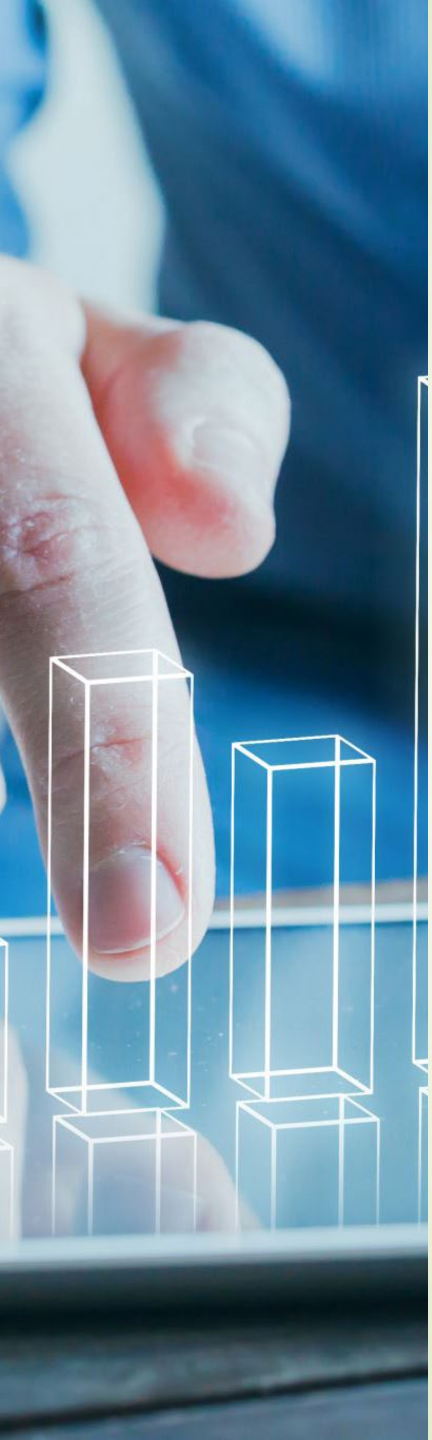
We also define **arbitrageurs/noise traders** as investors with top/bottom quintile **arbitrage scores.**

1.4 Which cryptos do arbitrageurs trade?

- We rank cryptos by fraction of the trading aligned with arbitrage direction
- Arbitrage activities concentrate on well-established tokens, like BTC and ETH (not on memecoins, like SHIB and DOGE)
- Trading volume for DOGE is high, suggesting noise trader activities.

1.5 Proxies for behavioral biases

- We focus on four behavioral biases (Liao et al., 2022; Sui and Wang, 2023; Kumar 2009; Barber and Odean, 2000):
  - extrapolation (DOX),
  - the disposition effect (DE),
  - lottery preference (LP), and
  - overtrade (Turnover) ➔ Yes, overtrade hurt arbitrageurs.
- We also construct an aggregated bias score by taking the average rank of these four biases.



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2.1 Investor Characteristics when sorted by Arbitrage scores

	rank	AS	Trading implied return (%)	Sharpe ratio	Composite bias index
Noise Trader		0.12	4.84	0.02	10.76
	2	0.61	4.88	0.03	11.82
	3	1.78	5.15	0.04	12.60
	4	6.93	5.27	0.07	13.32
Arbitrageur		87.20	5.70	0.14	13.77

arbitrageurs achieve **better** performance (return and Sharpe Ratio)

A striking positive arbitrage-bias relationship

2.2 Performance (weekly return) when double sorted by Arbitrage and Bias scores

Bias Score → Arbitrage Score ↓	Low	2	3	4	High	High - Low
Low	2.60	2.03	2.30	2.14	2.39	-0.21 (-0.95)
2	2.30	2.39	2.17	2.38	2.41	0.11 (0.49)
3	3.05	3.15	3.21	3.07	2.79	-0.26 (-5.98)
4	3.21	3.28	3.33	3.24	3.03	-0.17 (-8.12)
High	4.74	4.20	4.07	3.96	3.75	-0.99 (-5.47)
High - Low	2.14 (18.03)	2.17 (14.90)	1.77 (14.71)	1.82 (15.69)	1.36 (11.54)	

- Performance increases in AS, leading to significant HML (approximately **1% ~ 2% weekly returns**).

- Biases reduce performance.
- Bias has a much bigger impact on Arbitrageurs (**0.99% weekly returns**)

2.3 The cost of biases for arbitrageurs (weekly, market-adjusted returns)

	20-80 cutoff	
	(1)	(2)
arbitrageur	0.00900***	0.00832***
	(16.19)	(14.65)
noise trader	0.000454	0.000408
	(0.94)	(0.83)
unbiased	0.00190***	0.000931*
	(3.51)	(1.68)
biased	-0.00288***	-0.00289***
	(-5.67)	(-5.52)
arbitrage score		
bias score		
arbitrageur × Least_biased		0.00870***
		(4.77)
noise trader × Least_biased		0.00213
		(1.15)
arbitrage score × bias index		
Controls	Yes	Yes
Investor FE	Yes	Yes
Week FE	Yes	Yes
Observations	2,037,878	2,037,878
R-squared	0.196	0.196

Arbitrageurs outperform other investors by **0.83% weekly return**

20% most biased investors underperform others by **0.29% weekly return**

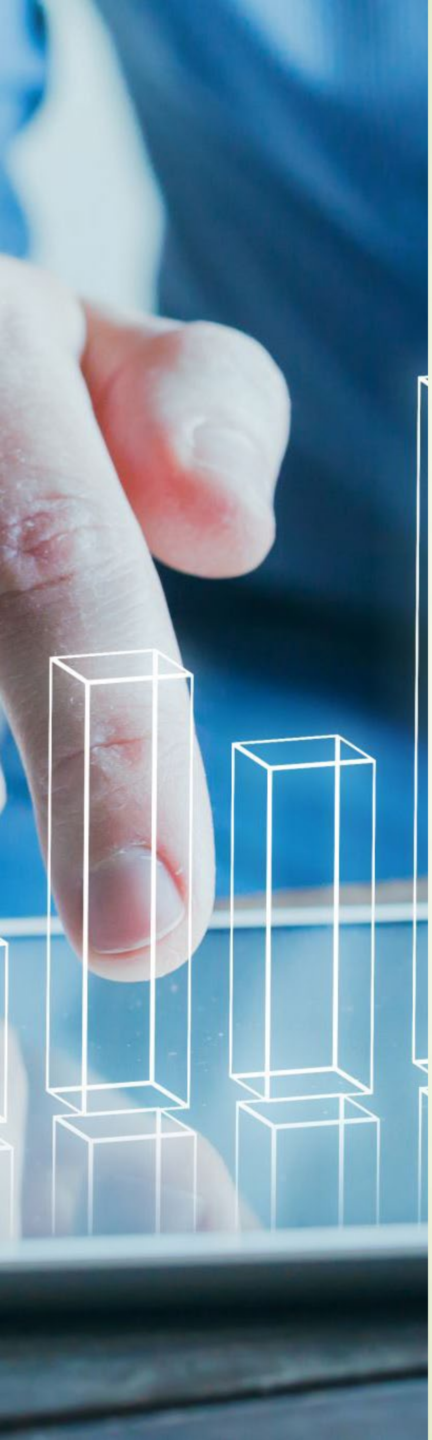
Least biased arbitrageurs outperform other arbitrageurs by **0.87% weekly return!**

2.4 Robust when using the values of scores

	Market-adjusted trading implied return (week)	
	(1)	(2)
arbitrage score	0.000109***	0.000223***
	(14.29)	(6.86)
bias score	-0.000531***	-0.000425***
	(-6.61)	(-5.15)
arbitrage score × bias index		-0.00000808***
		(-3.67)
Controls	Yes	Yes
Investor FE	Yes	Yes
Week FE	Yes	Yes
Observations	1,374,607	1,374,607
R-squared	0.199	0.199

The interaction term suggests a significant negative impact of bias on arbitrageurs' performance.

Our results are also robust to alternative thresholds of defining arbitrageurs and alternative definitions of arbitrage.



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3.1 The market efficiency implications

- **We focus on the C2 measure (Llorente et al. 2002)**
- $R_{it} = C_0 + C_1 \times R_{it-1} + C_2 \times R_{it-1} \times V_{it-1}$
  - R_{it} = asset return
  - V_{it-1} = lagged trading volume
- Economic interpretation:
  - $C_2 > 0$: the presence of informed trading
  - $C_2 < 0$: the presence of liquidity trading

3.2 C2 regression results

	C2		
	(1)	(2)	(3)
% Arbitrage Vol	0.695**		0.630**
	(2.680)		(2.714)
Arbitrage VW Bias		-0.0489**	-0.0452**
		(-2.283)	(-2.245)
Constant	-0.133	0.624***	0.274***
	(-1.018)	(3.507)	(2.868)
Token FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Observations	1,915	1,915	1,915
R-squared	0.268	0.269	0.274

- arbitrageurs' trading is associated with informed trading

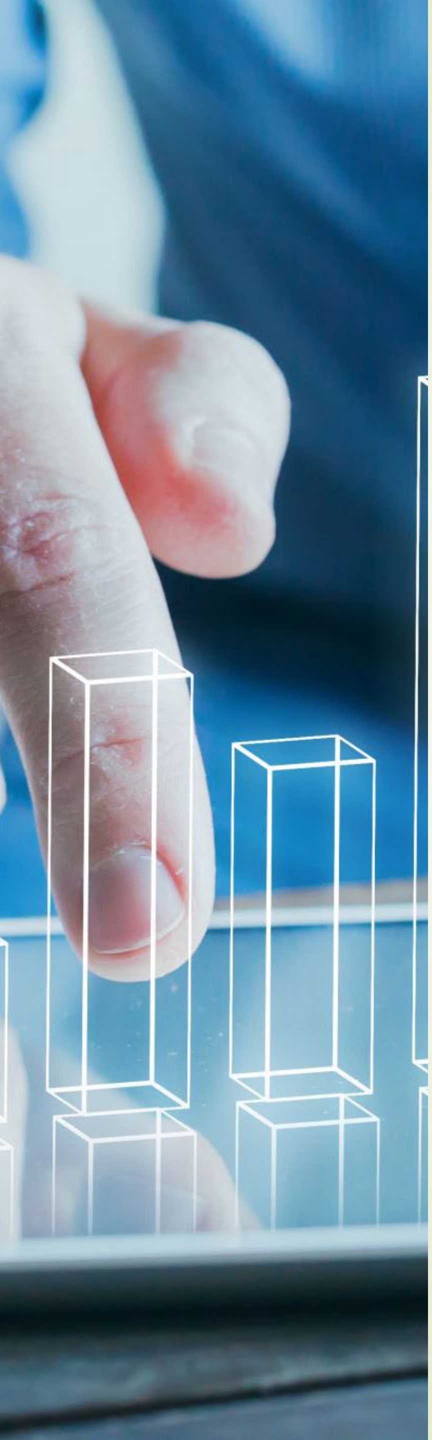
- But biased arbitrageurs' trading reduce informed trading

3.3 The impact of individual biases

	C2						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Arbitrage Vol	0.695**		0.630**	0.613***	0.578**	0.653***	0.620**
	(2.680)		(2.714)	(2.931)	(2.289)	(3.420)	(2.515)
Arbitrage VW Bias		-0.0489**	-0.0452**				
		(-2.283)	(-2.245)				
Arbitrage VW DOX				-0.0187			
				(-1.192)			
Arbitrage VW DE					-2.334***		
					(-2.913)		
Arbitrage VW LP						-0.309	
						(-0.568)	
Arbitrage VW Turnover							-0.00236
							(-1.494)
Constant	-0.133	0.624***	0.274***	0.0163	0.115	0.00330	-0.00543
	(-1.018)	(3.507)	(2.868)	(0.187)	(0.992)	(0.0252)	(-0.0417)
Token FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,915	1,915	1,915	1,915	1,915	1,915	1,915
R-squared	0.268	0.269	0.274	0.270	0.277	0.269	0.270

Among individual biases, the **disposition effect** has the biggest impact

Our results suggest that behavioral bias provides a novel type of Limits of arbitrage!



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4.1 Double sorting using trading cost-adjusted Performance (weekly return)

Bias Score → Arbitrage Score ↓	Low	2	3	4	High	High - Low
Low	3.98	3.64	3.86	3.75	4.25	0.26 (1.37)
2	3.91	4.14	4.20	4.29	4.15	0.23 (1.55)
3	4.35	4.65	4.67	4.75	4.36	0.01 (0.08)
4	4.76	4.70	4.98	4.77	4.51	-0.26 (-1.88)
High	6.07	5.41	5.03	4.89	4.59	-1.48 (-8.96)
High - Low	2.09 (12.38)	1.78 (10.99)	1.17 (7.75)	1.14 (7.21)	0.34 (1.79)	

- Performance increases in AS, though HML spread is slightly smaller (when compared to before fee perf)

- Biases reduce performance.
- Bias has an even bigger impact on arbitrageurs' perf (**1.48% weekly returns**)

4.2 The persistence of arbitrage trading

- We construct a transition matrix
- Each cell represents the weekly transition rate from one quintile (row) to another quintile (column) based on the Arbitrage Score

From/To	1 (noise trader)	2	3	4	5 (arbitrageur)
1 (noise trader)	**0.890338**	0.069912	0.022043	0.0107	0.007364
2	0.074994	0.787888	0.091449	0.02282	0.01613
3	0.026325	0.080389	0.7578	0.093299	0.026446
4	0.017753	0.020065	0.081886	0.773302	0.086815
5 (arbitrageur)	0.017904	0.017298	0.020504	0.071456	**0.838118**

Investors are most likely to stay in the same quintile, showing a **persistent** arbitrage ability

4.3 the effect of experience

	AS	rank_as	BS	rank_bs	Market-adjusted return (%)	
					Score	Rank
	(1)	(2)	(3)	(4)	(5)	(6)
Exp	21.29***	0.899***	-0.380***	-0.0670***	0.546	-0.402
	(40.36)	(48.42)	(-7.994)	(-3.329)	(1.425)	(-0.879)
Arb					0.0141**	0.299***
					(2.477)	(3.386)
Bias					-0.0296*	0.0931
					(-1.847)	(1.101)
Arb×Exp					0.0305***	0.343**
					(3.007)	(2.497)
Bias×Exp					-0.0454*	-0.167
					(-1.815)	(-1.265)
Arb×Bias					-0.000833**	-0.0676***
					(-2.143)	(-2.670)
Arb×Bias×Exp					-0.000344	0.0258
					(-0.490)	(0.642)
Constant	3.824***	2.760***	13.00***	3.108***	3.330***	2.384***
	(14.24)	(292.0)	(536.8)	(303.1)	(14.17)	(8.257)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,398,818	1,398,818	1,398,818	1,398,818	1,398,818	1,398,818
R-squared	0.400	0.599	0.514	0.508	0.198	0.197

The arbitrage score (bias) increases (decreases) with trading experience

Experienced investors profit more from arbitrage trades

However, experience does not seem to offset the neg return impact of biases on arbitrageurs.

Conclusions

- Arbitrageurs are not immune to behavioral biases. In fact, they exhibit a higher level of biases than noise traders.
- While arbitrageurs can generate superior performance, behavioral biases are more harmful to their performance.
- Behavioral biases of arbitrageurs also harm market efficiency: while arbitrageurs impound information into the prices, their biases impede this effect.

Thank you very much!

2.1 Stand-alone return impact
Arbitrage score

	Market-adjusted trading implied return (week)				
	(1)	(2)	(3)	(4)	(5)
AS	0.0000940***				
	(15.97)				
rank_as		0.0115***			
		(12.99)			
arbitrageur			0.00870***		0.00874***
			(15.71)		(15.77)
noise trader				0.000185	0.000677
				(0.38)	(1.40)
balance	-0.00451***	-0.00466***	-0.00458***	-0.00494***	-0.00459***
	(-32.28)	(-33.37)	(-32.86)	(-35.68)	(-32.87)
trade_num	-0.00000528***	-0.00000510***	-0.00000558***	-0.00000135	-0.00000547***
	(-5.20)	(-4.89)	(-5.38)	(-1.37)	(-5.25)
currency_num	-0.00603***	-0.00629***	-0.00611***	-0.00593***	-0.00609***
	(-16.47)	(-17.11)	(-16.68)	(-16.20)	(-16.60)
Investor FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Observations	2,037,878	2,037,878	2,037,878	2,037,878	2,037,878
R-squared	0.196	0.196	0.196	0.196	0.196

A one-stdev increase in *the Arbitrage score* is associated with **0.46%** higher weekly market-adjusted returns.

If we use dummy indicator, then **arbitrageurs** are associated with **0.87%** weekly returns.

2.1 Stand-alone return impact
Behavioral biases

	Market-adjusted trading implied return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
DOX	-0.000101***				-0.0000701***	
	(-5.54)				(-2.74)	
DE		-0.00113			-0.000950	
		(-1.15)			(-0.96)	
LP			-0.00351***		-0.00200***	
			(-6.62)		(-2.93)	
Turnover				-0.0000690***	-0.0000531***	
				(-7.37)	(-4.20)	
Aggregate bias score						-0.000477***
						(-5.94)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,037,878	1,420,219	2,037,878	1,374,607	1,374,607	1,420,219
R-squared	0.196	0.200	0.196	0.196	0.199	0.199

In general, behavioral biases **negatively** affect the portfolio returns