

The Impact of Spoofing on Bitcoin Market Microstructure

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June 16, 2026

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- Understanding spoofing is critical for market integrity and policy design.

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- 3 What are the economic incentives (profits) of spoofers?
- 4 How does spoofing affect market quality (liquidity, spreads, VPIN)?

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 - Deterioration of liquidity and market quality.

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 - Spoofing intensity and volume
 - Market quality: VPIN (Easley, López de Prado, and O'Hara (2012)), spreads

Order Imbalance and Returns

	R_t			
	[1-min]		[Hourly]	
Order book Bid-Ask imbalance, $Max[0, OBIB_t \times 10^{-2}]$	0.0173 (9.53) ***	0.0209 (11.45) ***	0.2963 (1.99) **	0.4079 (2.76) ***
Order book Ask-Bid imbalance, $- Min[0, OBIB_t \times 10^{-2}] $	0.0127 (4.92) ***	0.0143 (5.76) ***	0.5987 (2.42) **	0.5420 (2.39) **
Lagged order book Ask-Bid imbalance, $Max[0, OBIB_{t-1} \times 10^{-2}]$	-0.0081 (-5.37) ***	-0.0056 (-3.82) ***	-0.1188 (-0.72)	-0.2031 (-1.37)
Lagged order book Bid-Ask imbalance, $- Min[0, OBIB_t \times 10^{-2}] $	-0.0038 (-1.70)*	-0.0023 (-1.07)	-0.5082 (-2.28) **	-0.5252 (-2.20) **
Order imbalance, $OIB_t \times 10^{-2}$		0.0270 (13.85) ***		0.0118 (6.35) ***
Lagged return, R_{t-1}		-0.0255 (-2.57) ***		-0.0163 (-0.689)
Intercept	2.97×10^{-7} (0.05)	-6.54×10^{-6} (-1.31)	1×10^{-4} (0.46)	7.01×10^{-5} (0.266)
R^2	0.003	0.063	0.008	0.079
# of Observations	113937	113937	2173	2173

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- Positive OIB \Rightarrow upward price pressure; negative OIB \Rightarrow price decline.
- Evidence consistent across 1-minute and hourly horizons.

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 - 2 Median cancellation time < 1 second — high-frequency manipulation.

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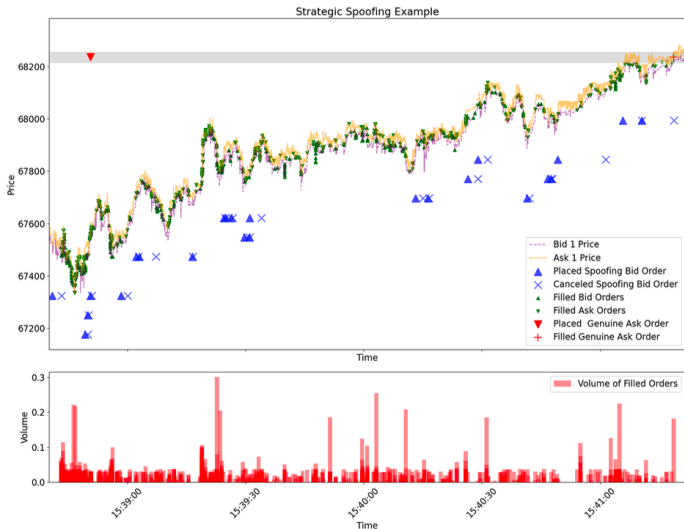
- **Validation:**

- Captures rapid, large, reversible quote bursts consistent with spoofing and market manipulation.
- Produces realistic spoofing distributions aligned with Lee et al. (2013) and Do and Putniņš (2023).

Spoofer Detection Illustration



Example of Spoofing Event



Bid spoofing on March 8, 2024 (15:39–15:42).
Price pumped from \$67,500 to \$68,200 before spoof cancellation.

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- Effects persist even after controlling for order imbalance and lagged returns.

Spoofer Intensity and Returns-Continued

	R_t			
Bid spoofing intensity, BSI_t	7.33×10^{-4} (13.71)***	6.05×10^{-4} (12.29)***		
Ask spoofing intensity, ASI_t	-9.56×10^{-4} (-7.46)***	-8.08×10^{-4} (-6.27)***		
Bid spoofing volume, BSV_t			6.53×10^{-4} (3.32)***	5.28×10^{-4} (2.97)***
Ask spoofing volume, ASV_t			-2.69×10^{-3} (-5.29)***	-2.50×10^{-3} (-4.69)***
Order book imbalance, $OBIB_t \times 10^{-2}$		1.40×10^{-2} (10.41)***		1.42×10^{-2} (10.53)***
Order imbalance, $OIB_t \times 10^{-2}$		2.63×10^{-2} (13.88)***		2.68×10^{-2} (14.01)***
Lagged return, R_{t-1}		-2.35×10^{-2} (-2.89)***		-2.19×10^{-2} (-2.72)***
Constant	2.25×10^{-6} (0.91)	-4.15×10^{-6} (-1.60)	5.58×10^{-6} (2.15)**	-1.39×10^{-6} (-0.52)

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Impact on Market Quality-Continued (1)

	Without spoofing activity	With spoofing activity	Difference
<i>VPIN</i>	0.55	0.78	0.23
<i>SPREAD</i>	12.01	12.22	0.21
<i>PQS</i>	0.021%	0.022%	0.001%

Impact on Market Quality-Continued (2)

Panel A:			
	VPIN	Spread	PQS
Const	0.58 (92.72)***	9.72 (72.92)***	1.79×10^{-4} (83.06)***
During Spoofing \times Spoofing Size	0.26 (10.54)***	0.98 (1.88)*	2.4×10^{-5} (2.88)***
After Spoofing \times Genuine Size	-0.45 (-9.48)***	-2.79 (-2.73)***	-2.9×10^{-5} (-1.77)*
Order imbalance $ OIB_t $	0.16 (40.26)***	-0.88 (-10.4)***	-5×10^{-6} (-3.54)***
Order book imbalance $ OBIB_t $	0.05 (3.02)***	0.72 (2.2)**	8×10^{-6} (1.52)
Trading Volume VOL_t	-1×10^{-6} (-36.0)***	1.4×10^{-5} (20.39)***	1×10^{-6} (15.6)***
Return $ R_t $	-35.53 (-9.0)***	2147.35 (25.46)***	0.037372 (27.44)***

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- Asymmetric effects suggest stronger price response to ask-side spoofing.

Profitability of Spoofing-Continued

	Bid spoofing profit, <i>BSP</i>		Ask spoofing profit, <i>ASP</i>	
Bid spoofing volume, \overline{BSV}_t	0.0026 (2.16)**	0.0027 (2.43)**		
Ask spoofing volume, \overline{ASV}_t			0.0095 (4.73)***	0.0055 (2.89)***
Order book imbalance, $\overline{OBIB}_t \times 10^{-2}$		-0.026 (-2.62)***		-0.02 (-1.28)
Order imbalance, $\overline{OIB}_t \times 10^{-2}$		0.0048 (0.93)		-0.0083 (-1.23)
Volatility, σ_t		5.70×10^{-6} (2.60)***		1.21×10^{-5} (3.84)***
Bid-ask spread, \overline{SPREAD}_t		2.60×10^{-5} (4.69)***		1.01×10^{-5} (1.26)
Spoofing length, \overline{SL}_i		7.07×10^{-6} (6.98)***		1.61×10^{-5} (9.86)***
Constant	0.0005 (37.28)***	5.47×10^{-5} (1.19)	0.0007 (32.25)***	5.28×10^{-5} (0.74)
R^2	0.004	0.178	0.024	0.181

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⇒ Confirms that spoofing signals false market pressure to induce opposite-side execution.

Robustness Tests

- To validate our spoofing intensity and volume measures, we conduct two robustness analyses following Do and Putniņš (2023):

- **Abnormal cancellations:** spoofing episodes are characterized by a high rate of order cancellations that would otherwise have executed within the same minute.

⇒ A one-unit increase in spoofing intensity leads to roughly 15 abnormal canceled bid orders per minute.

- **Trades opposing quotes:** spoofing activity on one side of the book triggers executions on the opposite side—bid spoofing leads to more sell-side trades, and ask spoofing to more buy-side trades.

⇒ Confirms that spoofing signals false market pressure to induce opposite-side execution.

- These tests demonstrate that our spoofing measures capture genuine manipulative behavior rather than mechanical order-book noise.

Conclusions

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- **Policy Implications:**
 - Detection frameworks can guide regulators (SEC, CFTC, FinCEN) in surveillance and enforcement.
 - Transparent order-book data and monitoring tools are essential for deterrence.

Thank you