NFT Markets and Asset Bubbles

HSG Alumni Event

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April 2023

ERC-20 Standard

- A basic and widely used standard (or template) for smart contracts on the Ethereum blockchain
- Mostly used to create altcoins and utility tokens for ICOs
- Requires the implementation of the following functions:
  - totalSupply
  - balanceOf
  - transfer
  - transferFrom
  - approve
  - allowance
- Wallets and exchanges use the standard to efficiently integrate tokens based on ERC-20 contracts

ERC-721 Standard

- The "non-fungible" version of ERC-20 tokens
- Mostly used for the creation of Non-Fungible Tokens (NFTs)
- Requires the implementation of the following functions:
  - totalSupply
  - ownerOf
  - transferFrom
  - approve
  - setApprovalForAll
  - ...
- Wallets and exchanges use the standard to efficiently integrate NFTs based on ERC-721 contracts

NFT Market

- The NFT market is worth over $22 billion
- The industry has grown 220× since 2021
- NFT sales hit $25 billion in 2021
- The NFT Market will be worth $80 billion by 2025

Our Paper in a Nutshell

- We identify $\sim$ 1,000 price run-up events in the NFT market
- A sharp price increase increases the probability of a crash, relative to the baseline
- Market-wide characteristics of the price run-ups can help predicting crashes
- Leveraging the blockchain transparency, we find that agent-based variables increase the prediction accuracy
- We identify a group of sophisticated agents, who consistently profit from run-ups and have the ability to time crashes

Data

- Transaction-level data for the 1,000 most traded NFT collections from OpenSea
- The sample period ranges from Jan 2021 to Sep 2022
- Large and comprehensive dataset
  - 15 million transactions
  - 1.3 million unique wallets
  - 20 billion USD trading volume
- The average price of an NFT in our sample is 0.92 ETH, equivalent to 2,000 USD

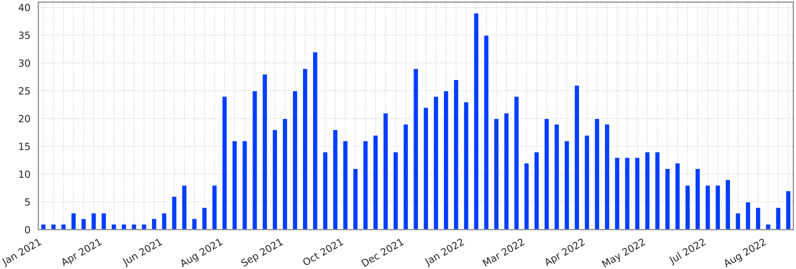
Price Run-Ups

- We define a **price run-up** as an episode in which the average sale price of an NFT collection have increased over 100% in the previous 24 hours

- Further, we require the trading volume during the event to be at least 10 ETH

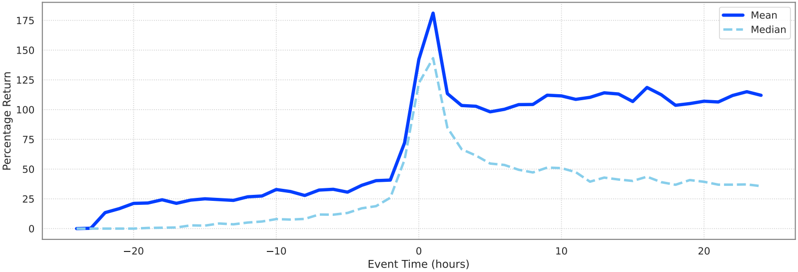
- We follow the definition of Greenwood et al. 2019 (*Bubbles for Fama*), but
  - We look at NFT collections, rather than US industry portfolios
  - We use high-frequency (hourly) returns, rather than monthly
  - Our window is 24 hours, rather than 2 years
  - Our sample is much larger and includes transaction-level data

Identified Run-Up Events



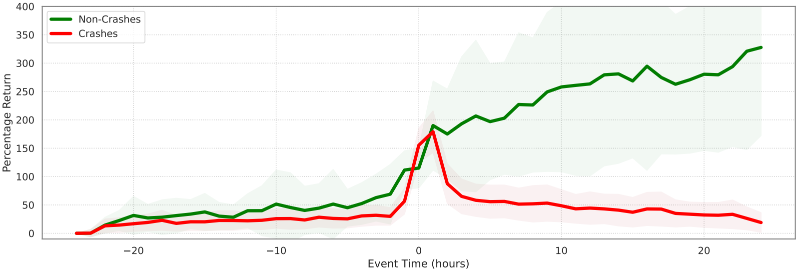
- We identify 1,017 non-overlapping price run-up events
- The average number of participants is 1,300
- The average trading volume is 1.5 million USD

Event Returns



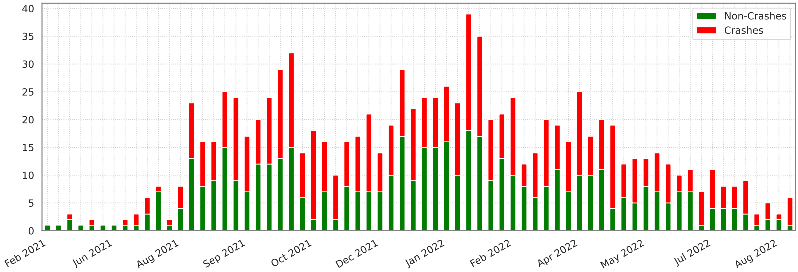
- Centered at $t = 0$, the hour in which the run-up is identified
- The event-time cumulative returns are, on average, positive for $t \in [1, 24]$
- Mean $>>$ Median $\implies$ event returns are highly skewed

Event Returns - Crashes and Non-Crashes



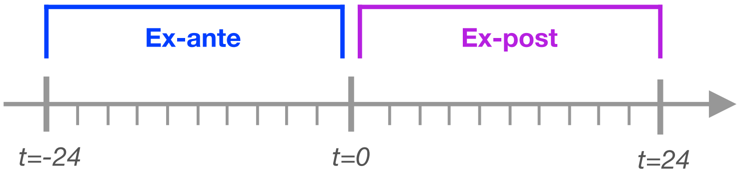
- An event is a "**crash**" if the ex-post return is lower than -40% after 24 hours
- About 52% of the events result in a crash, ex-post
- Cumulative returns show a wide wedge between the two categories

Identified Run-Up Events



- Crashes are evenly distributed in our sample: no significant clustering
- No aggregate factor is driving the formation of bubbles

Predicting Crashes



We define the following market-wide variables, computed in the ex-ante window

- **Volatility:** Standard deviation of hourly returns
- **Turnover:** Number of sales divided by circulating supply
- **Age:** Number of hours since the collection's launch
- **Acceleration:** Difference $R(-24, 0) - R(-24, -12)$

Predicting Crashes with Market-Wide Variables

Dep. Variable	Crash	Crash	Crash	Crash	Crash
Volatility	0.4401***				0.2714***
	(7.2525)				(4.5709)
Turnover		-0.3768***			-0.3199***
		(-5.5371)			(-5.5626)
Age			0.0001***		0.0001***
			(4.0524)		(3.1493)
Acceleration				0.1668***	0.1594***
				(11.344)	(10.557)
Intercept	0.2582***	0.5431***	0.4751***	0.3335***	0.1669***
	(6.6416)	(30.182)	(24.898)	(15.626)	(3.9723)
Observations	1,017	1,017	1,017	1,017	1,017
R-squared	0.0468	0.0192	0.0217	0.1601	0.2110

Agent-Based Variables

- All NFT transactions are on the blockchain, providing a high level of transparency
- We observe the wallet ids of buyer and sellers
  - We can track activity and profitability across events
  - We can check the entire activity on other DeFi platforms
- Can we leverage these data to improve the ex-ante identification of bubbles?
- We will focus on 3 agent-based metrics at the event-level
  1. Percentage of sophisticated investors participating
  2. Ownership concentration (number of unique owners)
  3. Amount of wash trading

1 – Sophisticated Agents

- We compute agents' profits during run-up events, finding significant persistence of their performance over time, across different events
- We define **sophisticated agents** as those who performed well in previous events
- We require at least 25% profits during the 5 previous run-ups, on average
- Sophisticated agents make up for 12% of the investors participating in run-ups

Characteristics of Sophisticated Agents

- How do sophisticated investors differ from others?

	Sophisticated	Others	Difference	t-stat
NFT Market				

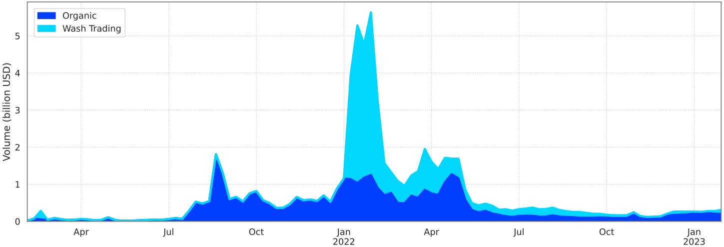
2 – Ownership Concentration

- The **fraction of unique owners** is a key metric displayed in OpenSea

$$\frac{\#\text{ of wallets holding an NFT of the collection}}{\#\text{ of NFTs available}}$$

3 – Wash Trading

- **Wash trading:** artificially inflate volume by repeatedly trading tokens



- We identify wash-trading transactions, with the two-sided purpose of
  1. Computing an additional agent-based predictor of crashes
  2. Testing the robustness of our results to the presence of wash trading

3 – Wash Trading

- We use the method proposed by Hildobby (2022), which enables a transaction-level identification of wash trading
- The methodology involves applying four filters
  1. The buyer and seller wallet addresses are identical
  2. Pair of trades with seller and buyer inverted for the same NFT
  3. Same address has bought three or more times the same NFT
  4. The addresses which funded the buyer and seller are identical or are one another
- We find 33,293 transactions – 0.23% of the sample trading volume of 63 million – 0.35% of the total
- 3rd agent-based variable: the amount of wash trading before the run-up event

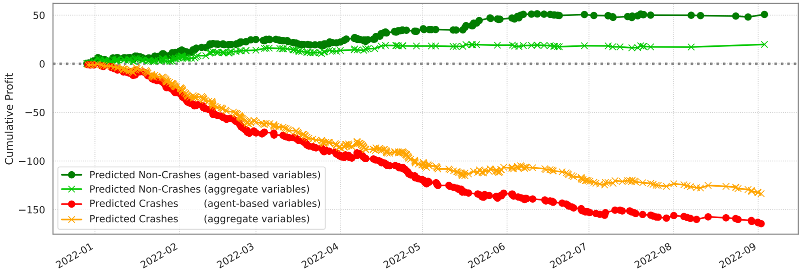
Predicting Crashes with Agent-Based Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Crash	Crash	Crash	Ex-Post Return	Ex-Post Return	Ex-Post Return
Sophisticated	-0.5114***		-0.4155***	2.1993***		1.7250***
	(-3.4262)		(-2.8422)	(4.8323)		(3.8923)
Unique Owners	-0.0114*		-0.0070	0.0585***		0.0403**
	(-1.8545)		(-1.0926)	(3.1115)		(1.9849)
Wash Trading	0.0770***		0.0613***	-0.2718***		-0.1988***
	(6.6193)		(5.0739)	(-7.7302)		(-6.4099)
Market-wide Variables	No	Yes	Yes	No	Yes	Yes
Intercept	0.5183***	0.1669***	0.2400***	-0.6695***	0.9322***	0.5826***
	(15.389)	(3.9723)	(4.8339)	(-7.1665)	(8.5946)	(4.0961)
Observations	1,017	1,017	1,017	1,017	1,017	1,017
R-squared	0.0700	0.2110	0.2391	0.1263	0.3641	0.4101

Economic Magnitude

- To estimate the economic value of crash predictability, we construct a simple trading strategy based on predictions from our regression model
- First, we fit the cross-sectional model to predict crashes, using only data from events realized in 2021
- Then, we produce out-of-sample predictions for events of 2022
- Track two portfolios, buying at $t = 1$ and selling at $t = 24$
  - Predicted Non-Crashes: If the prediction is below median
  - Predicted Crashes: If the prediction is above median

Strategy Returns



- Using only market variables variables:
  - Profit of 19 ETH vs loss of 133 ETH
- Adding agent-based variables:
  - Profit of 50 ETH vs loss of 164 ETH

Liquidity Dry-Ups

- Crashes exhibit liquidity dry-ups ex-post

Dep. Variable	Turnover	Amihud	Volatility	Turnover	Amihud	Volatility	Turnover	Amihud	Volatility
Crash Dummy	-0.03***	0.0***	0.11***						
	(-6.04)	(3.23)	(7.09)						
Unique Owners				0.01***	-0.0***	-0.02***			
				(5.58)	(-4.93)	(-6.43)			
Wash Trading							-0.01***	0.01	0.02***
							(-8.63)	(1.18)	(2.85)
Intercept	0.04***	0.01***	0.48***	0.02***	0.01***	0.56***	0.04***	0.01***	0.51***
	(9.53)	(5.10)	(35.57)	(8.51)	(12.14)	(50.46)	(10.89)	(8.25)	(40.57)
Observations	1,017	1,017	1,017	1,017	1,017	1,017	1,017	1,017	1,017
R-squared	0.04	0.01	0.05	0.12	0.01	0.04	0.06	0.00	0.01

- *Unique Owners* and *Wash Trading* forecast future illiquidity

Conclusions

- Ex-ante market-wide characteristics of price run-ups can predict ex-post crashes
- Agent-based variables improve the forecasting accuracy
- The economic magnitude of crash predictability is large, especially when agent-based variables are included as predictors
- Our results are consistent with the empirical evidence on US and international industry portfolios (Greenwood et al., 2019)
- Sophisticated investors consistently outperform their peers, with indication of superior information and timing skills