The Economics of Non-Fungible Tokens

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This Paper

- Understand the returns of the overall NFT market
- Construct a NFT index
- Study the properties of the index, the market and the investors

What is a NFT?

- A non-fungible token (NFT) is a *unique* digital identifier that cannot be copied, that is recorded in a *blockchain*, and that is used *to certify authenticity and ownership*
- Ownership can be transferred, allowing NFTs to be sold and traded
- NFTs have the potential of being the property rights for the digital economy

Results Preview

- Repeat sales regression method (RSR)
  - 1.0% average weekly return, 14.6% volatility, 0.494 Sharpe ratio
- Predictions
  - market segmentation: top buyers $\approx$ 30% portfolio in one collection and purchase $\approx$ 7% of NFTs from single seller
  - rarity: rare NFTs in one collection have $\approx$ 18% higher prices
  - investor characteristics
    - experience matters for performance
    - flippers vs. collectors
  - search frictions (not in presentation, see paper)
- Predictability: time-series & cross-sectional (not in presentation, see paper)

Data and Methodology

Data

- Major exchanges:
  - CryptoKitties
  - Gods Unchained
  - Decentraland
  - OpenSea
  - Atomic
- Cross-checked with blockchain
- Aggregate to weekly data
- Trades in ETH, WETH, MANA, USD

Hedonic regressions to study determinants of valuation (I/II)

- Hedonic regressions decomposes the characteristics of similar heterogenous assets, and give them separate values:

$$p_{it} = b_t + \sum_{k=1}^{K} \beta_k z_{itk} + \epsilon_{it}$$

  where p is the logged price, b_t denote time dummies, and z denotes the quantity associated with characteristics k.

- The β_k estimates provide information on the determinants of NFT valuations.

Hedonic regressions to study determinants of valuation (II/II)

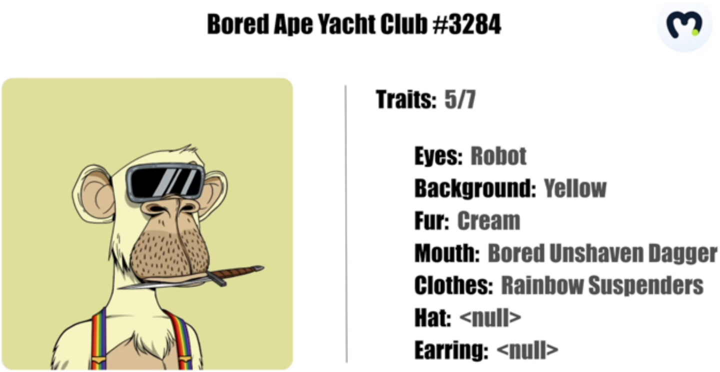
- Full sample: time, currency, collection and repeat sale dummies
- Collection sample: add NFT characteristics
  - trait ratio: number of available traits as fraction of total number of traits
  - rarity: based on number of NFT in collection with same features in traits.

How to measure NFT rarity?

- To measure a NFT rarity you first need details about a given collection:
  - number of different traits (layers),
  - number of NFTs in the collection,
  - how many NFTs have a particular feature or attribute.

An example using the BAYC collection

- BAYC has 10,000 NFTs randomly created on the basis of seven layers.
- In the image below the BAYC with id # 3284



BAYC collection traits

- For the BAYC collection, the seven traits are:
  1. Eyes
  2. Background
  3. Fur
  4. Mouth
  5. Clothes
  6. Hat
  7. Earring
- Not all NFTs in the collection have all the seven traits
  - The trait ratio is the number of non-null traits as a fraction of the number of available traits in a collection. For BAYC # 3284 the trait ratio is $5/7$.
- Each trait has different possible features or attributes (e.g., Eyes: Robot).

Rarity percentage and score

- To build a measure of rarity of a NFT in a collection, we first compute the rarity percentage for each of its trait i as:

$$\text{Rarity Percentage}_i = \frac{\text{Number of NFTs with feature } j \text{ in Trait } i}{\text{Number of NFTs in collection}}$$

- For example, if only 10 Apes have Eyes: Robot we would have:

$$\text{Rarity Percentage}_{\text{Eyes}} = \frac{10}{10,000}$$

- We build a rarity score for trait i of the NFT in a collection as the inverse of the rarity percentage:

$$\text{Rarity Score}_i = \frac{1}{\text{Rarity Percentage}_i}$$

Rarity score robot-eyes for the BAYC collection

Bored Ape Yacht Club #3284

Eyes: Robot

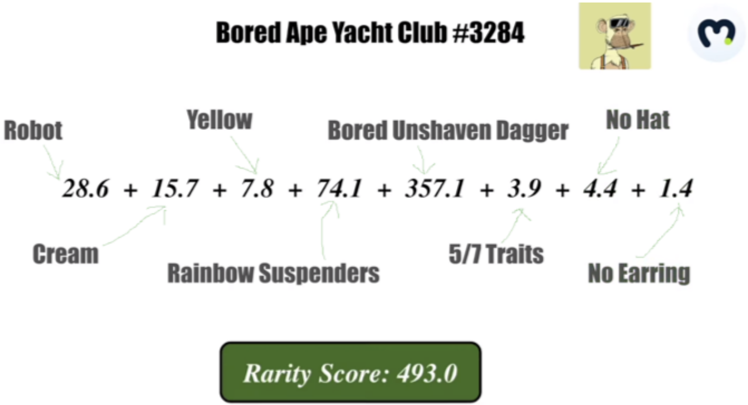
$$\frac{350}{10\,000} = 3.5\%$$

Rarity Percentage

$$\frac{1}{0.035} = 28.6$$

Rarity Score

Rarity score for BAYC #3284



A higher value for the rarity score is associated with a less common (more rare) NFT part of a collection.

Hedonic regressions: full sample

	(1)	(2)	(3)	(4)
Time Dummies	Y	Y	Y	Y
Currency Dummies	N	Y	Y	Y
Collection Dummies	N	N	Y	Y
Repeat Dummy	N	N	N	0.091
				(145.71)
N	21,198,053	21,198,053	21,198,044	21,198,044
R^2	0.4419	0.4478	0.7965	0.7965

The table shows hedonic regression results. The dependent variable is the natural log of NFT prices. t-statistics are in parenthesis.

Hedonic regressions: collection sample

	(1)	(2)	(3)	(4)	(5)	(6)
Time Dummies	Y	Y	Y	Y	Y	Y
Currency Dummies	Y	Y	Y	Y	Y	Y
Collection Dummies	Y	Y	Y	Y	Y	Y
Repeat Dummy	0.025	0.024	0.026	0.027	0.026	0.026
	(35.04)	(32.40)	(35.89)	(37.14)	(36.24)	(35.98)
NFT Characteristics						
Trait Ratio	N	-0.451	N	N	N	N
		(-114.17)				
Rarity 1	N	N	0.184	N	N	N
			(195.49)			
Rarity 2	N	N	N	0.184	N	N
				(195.49)		
Rarity 3	N	N	N	N	0.171	N
					(161.94)	
Rarity 4	N	N	N	N	N	0.174
						(177.14)
N	9,156,886	8,566,871	8,881,081	8,881,081	8,881,081	8,881,081
R^2	0.8297	0.8395	0.8380	0.8378	0.8378	0.8379

details about rarity measures creator sample

Repeat Sales Regression Method (I/II)

- There are T time periods and sales can occur in any of the periods from 0 to T. We denote t as the subscript for the time period (in our baseline specification, a time period is a week).

- For a pair of sales of a given NFT i, prices and the NFT market index are assumed to be related as in the following equation:

$$\frac{P_{it'}}{P_{it}} = \frac{B_{t'}}{B_t} U_{itt'}$$

  where P_{it} is the transaction price of NFT i at time period t.

- For a pair of sales, t is the time at the purchasing transaction and t' is the time at the sale transaction, and $t' > t$. B_t is the general NFT market price index at time t and $U_{itt'}$ is the multiplicative error term for the price pair as discussed above.

Repeat Sales Regression Method (II/II)

The model can then be converted to the logged scale, which is the basis of the estimation:

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + u_{itt'}$$

Why RSR?

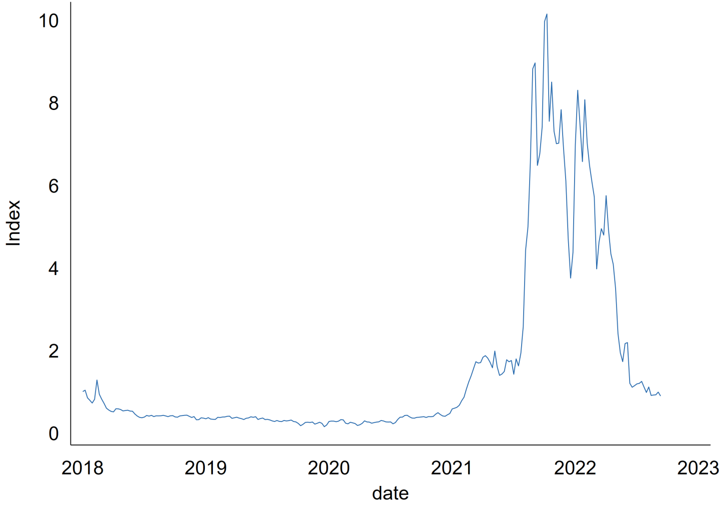
- Mean/Median/floor price
- Hedonic regression
- Repeat sales regression

Explanatory Power

	Full Sample	CryptoKitties	CryptoPunks
R-squared	0.266	0.313	0.669
Observations	4,953,111	313,049	10,077

	Bored Ape	Sup Ducks	Decentraland
R-squared	0.910	0.886	0.566
Observations	13,663	6,876	11,547

NFT Market Index



collection indices summary stats exposure predictability

Market segmentation and testable predictions

▸ predictability ▸ search frictions

Market segmentation (I/II)

- Collect wallet ID of buyer/seller for each NFT transaction.
- Measures of market segmentation:
  - the share of the top buyers' portfolio invested in their largest holding by collection:
    - ⋆ N_{ic}: NFTs from collection c in portfolio of buyer i
    - ⋆ for buyer i: $\mathcal{S}_i^{max} = N_{ic}^{max} / \sum_c N_{ic}$
  - the share of the top buyers' portfolio purchased from their single largest seller.

Example

- Consider buyer with wallet ID: `0xe07e2a56849f1d31233df11710c00e5a526c59aa` who bought 11 NFTs who was active in 6 weeks of 2022.
- NFT purchases by collections: 5 “Mythicals origins”; 1 “PharaGods”; 1 “Molly the Influencer”; 3 “Molly Nft Official” and 1 “Molly Secret Collection”.
- In this case, the collection ratio is: $5/11 \approx 45\%$.
- The buyer bought from the same seller 2 NFTs and the rest from 9 different sellers: the seller ratio is: $2/11 \approx 18\%$

Market segmentation (II/II)

Total buyers = 1,877,975 Total Transactions = 21,350,937

Raw: Collection		Net of Collection Ratio		Seller	
Top 10k buyers	0.267	Top 10k buyers	0.264	Top 10k buyers	0.059
Top 100k buyers	0.300	Top 100k buyers	0.298	Top 100k buyers	0.079

Top buyers account to 25-58% of total transactions and have a concentrated portfolio ($\approx$ 30% in one collection) and purchase a large fraction of their NFTs from a single seller ($\approx$ 7%).

Notes: "net of collection ratio" accounts for the number of NFT transactions in each collection.

Predictions about investors

- **Experienced investors outperform inexperienced investors**: test for number of buys
    - ⋆ Oh, Rosen and Zhang (2022): experienced investors make 8.6 pp more per trade in the NFT market (mostly due to participation in primary market).
- **Negative correlation between holding period and returns**: test for average trading gap
    - ⋆ Lovo and Spaenjers (2018): collectors pay more, hold longer, and are more likely to sell in distress at a low price.
- **Negative correlation between investor under-diversification and returns**: test for share of buyer top collection transaction net of share of collection transaction over total.
    - ⋆ Goetzmann and Kuman (2008): in the U.S. equity market under-diversification is greater among less-sophisticated investors.

Investor

Based on repeat sales regressions.

	r	r	r	r
$\log(\#buy)$	0.022***	0.004***	0.010***	0.011***
	(162.31)	(23.18)	(51.89)	(53.63)
$FirstSale$		0.158***	0.246***	0.245***
		(127.34)	(165.52)	(164.91)
$\log(avggap)$			-0.062***	-0.059***
			(-107.33)	(-97.00)
$Ratio^{diff}$				-0.018***
				(-13.85)
N	4,953,111	4,953,111	4,953,111	4,953,111
R^2	0.2694	0.2695	0.2695	0.2735

Conclusion

Conclusion

- Construct indices for the NFT market
- Overall summary statistics
- Predictions in terms of assets, market and investors

Backup Slides

Formulas

- Notation:
  - N_C: number of NFTs in collection
  - N_T: number of traits in collection
  - $N_{T_{kj}}$: number of NFTs in collection with feature j in trait k
- Rarity score for a single NFT in a collection with feature j in trait k:

$$RS = \sum_{k=1}^{N_T} \frac{NC}{N_{T_{kj}}} \tag{1}$$

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Rarity scores

1. rarity score: see Equation (1)
2. min rarity score: $\min NC/N_{T_{kj}}$
3. max rarity score: $\max NC/N_{T_{kj}}$
4. standard deviation rarity score: $\sigma(NC/N_{T_{kj}}))$

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Hedonic regressions: creator sample

	(1)	(2)	(3)
Time Dummies	Y	Y	Y
Currency Dummies	Y	Y	Y
Collection Dummies	N	N	N
Repeat Dummy	N	N	N
Creator Characteristics			
$log(Fee + 1)$	N	0.050	N
		(97.43)	
Creator Dummies	N	N	Y
N	2,765,292	2,765,292	2,765,292
R^2	0.2693	0.2718	0.6996

The table shows hedonic regression results. The dependent variable is the natural log of NFT prices. t-statistics are in parenthesis.

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Exposures of NFT Market

Traditional Asset Market

Gold	0.906			
	(1.325)			
BBG Commodity		1.861***		
		(2.895)		
Dollar			-1.821	
			(-1.077)	
Carry				2.707
				(1.583)
α	0.023*	0.024*	0.025*	0.025*
	(1.757)	(1.815)	(1.869)	(1.855)
R-squared	0.008	0.039	0.006	0.012

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NFT Coins

	$R^{Coins} - R^f$	$R^{Coins} - R^f$
$R^{NFT} - R^f$	0.333***	0.146**
	(5.408)	(2.105)
CMKTRF		0.737***
		(6.250)
α	0.017	0.019*
	(1.419)	(1.729)
R-squared	0.125	0.263

$R^{Coins} - R^f$	+1	+2	+3	+4	+5	+6
$R^{NFT} - R^f$	0.229***	0.330**	0.328	0.311	0.297	0.391
	(3.077)	(2.553)	(1.585)	(1.239)	(1.064)	(1.042)
CMKTRF	-0.239	-0.012	0.144	0.406	0.743	0.810
	(-1.625)	(-0.053)	(0.404)	(1.139)	(1.359)	(1.200)
R-squared	0.042	0.042	0.028	0.028	0.031	0.027

Cryptocurrency Market

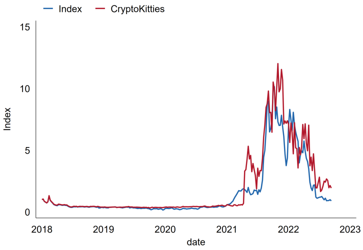
	(1) $R^{NFT} - R^{f}$	(2) $R^{NFT} - R^{f}$
CMKTRF	0.497***	0.502***
	(6.12)	(6.15)
CSIZE		0.106
		(0.87)
CMOM		0.067
		(0.51)
α	0.007	0.06
	(0.86)	(0.62)
R-squared	0.134	0.138

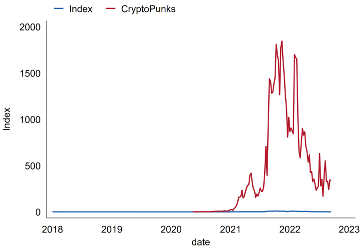
more on exposure

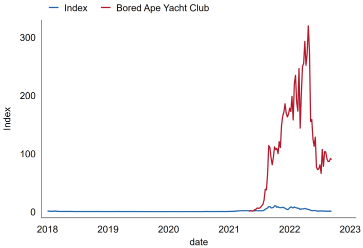
Traditional Asset Market

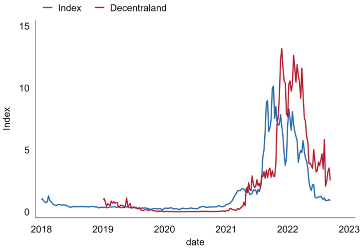
MKTRF	0.693*	0.897**	0.952***	0.876**	0.888**
	(1.955)	(2.500)	(2.617)	(2.350)	(2.376)
SMB		-0.674	-0.547	-1.421**	-1.347*
		(-1.085)	(-0.860)	(-2.005)	(-1.862)
HML		1.296***	1.446***	1.788***	1.937***
		(3.302)	(3.413)	(2.987)	(2.928)
MOM			0.365		0.222
			(0.942)		(0.534)
RMW				-2.026	-1.969
				(-2.443)	(-2.350)
CMA				0.227	0.004
				(0.204)	(0.03)
α	0.008	0.008	0.008	0.010	0.008
	(0.885)	(0.922)	(0.913)	(1.097)	(0.922)
R-squared	0.016	0.058	0.062	0.082	0.058

Some Collection Indices









Summary Statistics

Panel A	Mean	SD	Median	Skewness	Kurtosis	10%	90%	SR (annual)
NFT	0.010	0.146	0.006	0.943	6.719	-0.140	0.169	0.494
NFTH	0.011	0.150	0.006	0.863	6.221	-0.144	0.195	0.529
CMKTRF	0.005	0.110	0.004	-0.133	3.925	-0.137	0.144	0.328
MKTRF	0.002	0.026	0.006	-0.734	5.544	-0.032	0.028	0.555
Panel B		NFT	NFTH				NFT	NFTH
2018Q1		-3.51%	-3.50%		2020Q2		3.46%	3.55%
2018Q2		-2.44%	-2.39%		2020Q3		3.50%	3.63%
2018Q3		1.12%	1.42%		2020Q4		1.88%	1.78%
2018Q4		-0.86%	-0.43%		2021Q1		10.67%	10.42%
2019Q1		0.42%	0.14%		2021Q2		0.88%	1.39%
2019Q2		-0.66%	-0.68%		2021Q3		14.50%	14.31%
2019Q3		-1.30%	-1.14%		2021Q4		-2.57%	-2.63%
2019Q4		-0.74%	-0.59%		2022Q1		2.80%	2.89%
2020Q1		0.86%	1.34%		2022Q2		-8.55%	-8.58%

Time-Series Return Predictability

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Candidates

- Volatility
- Valuation ratio: Index/Trans
- Attention
- Serial dependence: Momentum/Reversal
- Volume

Volatility

	+1	+2	+3	+4	+5	+6	+7	+8
Vol	-0.045	-0.119	-0.197	-0.287	-0.368*	-0.483*	-0.606**	-0.739**
	(-0.590)	(-0.875)	(-1.170)	(-1.510)	(-1.690)	(-1.906)	(-2.113)	(-2.346)
R-squared	0.003	0.008	0.015	0.025	0.034	0.049	0.065	0.084

- A one-standard-deviation increase in *Vol* $\rightarrow$ 14.8% decrease in cumulative NFT market return at eight-week horizon

Valuation Ratio

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
$\log(\mathit{Index}/\mathit{Trans})$	-0.061***	-0.120***	-0.164***	-0.203***	-0.239***	-0.271***	-0.309***	-0.339***
	(-3.698)	(-3.589)	(-3.272)	(-3.350)	(-3.591)	(-3.693)	(-3.846)	(-3.772)
R-squared	0.071	0.124	0.152	0.177	0.206	0.228	0.255	0.269
Panel B	+1	+2	+3	+4	+5	+6	+7	+8
$\log(\mathit{Index}/\mathit{Trans})$	-0.066***	-0.122***	-0.162***	-0.196***	-0.232***	-0.262***	-0.289***	-0.307***
	(-4.156)	(-3.701)	(-3.301)	(-3.361)	(-3.697)	(-3.763)	(-3.647)	(-3.460)
Vol	-0.031	-0.101	-0.176	-0.258	-0.330	-0.440	-0.561*	-0.697**
	(-0.435)	(-0.763)	(-1.043)	(-1.286)	(-1.385)	(-1.573)	(-1.771)	(-2.020)
R-squared	0.084	0.138	0.168	0.198	0.234	0.263	0.285	0.297

- A one-standard-deviation increase in $\log(\mathit{Index}/\mathit{Trans}) \rightarrow 19.1\%$ decrease in cumulative NFT market return at five-week horizon

Attention

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{NFT}$	0.023	0.019	0.010	0.016	0.018	0.017	0.029	0.021
	(1.558)	(0.688)	(0.247)	(0.353)	(0.346)	(0.288)	(0.464)	(0.289)
R-squared	0.010	0.003	0.001	0.001	0.001	0.001	0.002	0.001
Panel B	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{Crypto}$	0.013	0.005	0.016	0.022	0.032	0.043	0.032	0.018
	(0.830)	(0.177)	(0.380)	(0.375)	(0.410)	(0.457)	(0.305)	(0.155)
R-squared	0.004	0.000	0.002	0.003	0.005	0.008	0.004	0.001
Panel C	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{Bitcoin}$	-0.002	0.001	0.008	0.018	0.041	0.057	0.072	0.076
	(-0.139)	(0.031)	(0.197)	(0.304)	(0.581)	(0.689)	(0.756)	(0.722)
R-squared	0.000	0.000	0.000	0.002	0.007	0.012	0.016	0.016

Serial Dependence

	+1	+2	+3	+4	+5	+6	+7	+8
$R^{NFT} - R^f$	-0.039	-0.188	-0.273	-0.346	-0.284	-0.152	-0.081	-0.122
	(-0.247)	(-0.614)	(-0.683)	(-0.718)	(-0.554)	(-0.287)	(-0.158)	(-0.240)
R-squared	0.000	0.005	0.007	0.008	0.004	0.001	0.000	0.001

Volume

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
Volume	0.054***	0.072**	0.090*	0.098	0.081	0.080	0.088	0.076
	(2.901)	(2.040)	(1.727)	(1.455)	(1.019)	(0.903)	(0.900)	(0.727)
R-squared	0.041	0.033	0.035	0.031	0.017	0.015	0.015	0.010
Panel B	**+1**	**+2**	**+3**	**+4**	**+5**	**+6**	**+7**	**+8**
Volume	0.039*	0.042	0.049	0.044	0.015	0.002	-0.003	-0.025
	(1.863)	(1.216)	(0.993)	(0.734)	(0.210)	(0.024)	(-0.038)	(-0.308)
log (*Index*/*Trans*)	-0.059***	-0.115***	-0.153***	-0.189***	-0.230***	-0.261***	-0.289***	-0.312***
	(-3.833)	(-3.579)	(-3.248)	(-3.333)	(-3.724)	(-3.823)	(-3.723)	(-3.540)
Vol	-0.013	-0.081	-0.153	-0.237	-0.323	-0.439	-0.562*	-0.708**
	(-0.177)	(-0.602)	(-0.904)	(-1.203)	(-1.392)	(-1.605)	(-1.810)	(-2.103)
R-squared	0.105	0.149	0.178	0.204	0.235	0.263	0.285	0.298

Cross-Sectional Return Predictability

Size & Serial Dependence

- Further examine cross-sectional return predictability
- Size/masterpiece effect
- Serial dependence: Momentum/Reversal

Size

- Size/masterpiece effect

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma \times (t' - t) \ln P_{i,t} + u_{itt'}$$

Size

	Full Sample	CryptoKitties	CryptoPunks
$(t' - t) \ln P$	-0.005***	-0.001***	-0.001
	(-14.092)	(-14.348)	(-0.834)

	Bored Ape	Sup Ducks	Decentraland
$(t' - t) \ln P$	-0.002*	-0.011***	-0.013***
	(-1.804)	(-3.327)	(-21.991)

- Doubling the logged NFT purchase price is associated with a 0.5% decrease in the weekly return (26% annually)

Serial Dependence

- Testing for serial dependence

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma \left(t' - t\right) r_{i,b} + u_{itt'}$$

Serial Dependence

	Full Sample	CryptoKitties	CryptoPunks
$(t' - t)\, r_{i,t}$	-0.013***	-0.004***	-0.089***
	(-8.062)	(-8.774)	(-2.760)

	Bored Ape	Sup Ducks	Decentraland
$(t' - t)\, r_{i,t}$	-0.016***	-0.017**	-0.012***
	(-3.453)	(-2.821)	(-4.566)

- A 10% increase in average weekly return in the NFT's previous repeat sale is associated with an 0.13% decrease in the weekly return (6.8% annually)

Search frictions, asset illiquidity and holding periods (I/II)

- For non-fungible and illiquid assets, when investors have private valuations, a short-horizon transaction results only when an investor meets another with a higher valuation (see Sagi (2021)).
- Randomness in matching and bargaining implies that return variance does not vanish as the observed holding period horizon goes to zero.
  - Lovo and Spaenjers (2018) has a similar prediction due to the uncertainty in the distribution of bidders.
- We should expect that the idiosyncratic mean and variance of NFT logged price appreciation have a *positive* intercept.

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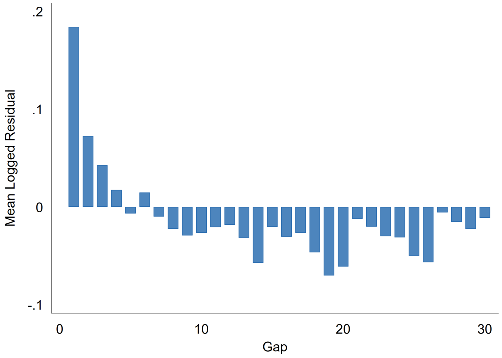
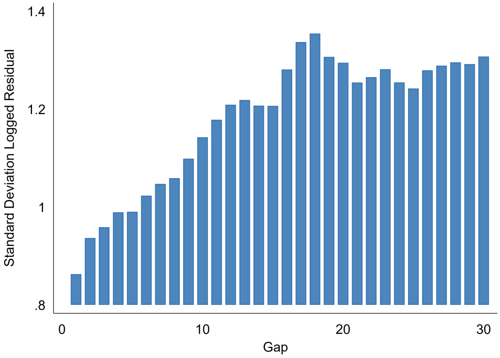
Search frictions, asset illiquidity and holding periods (II/II)



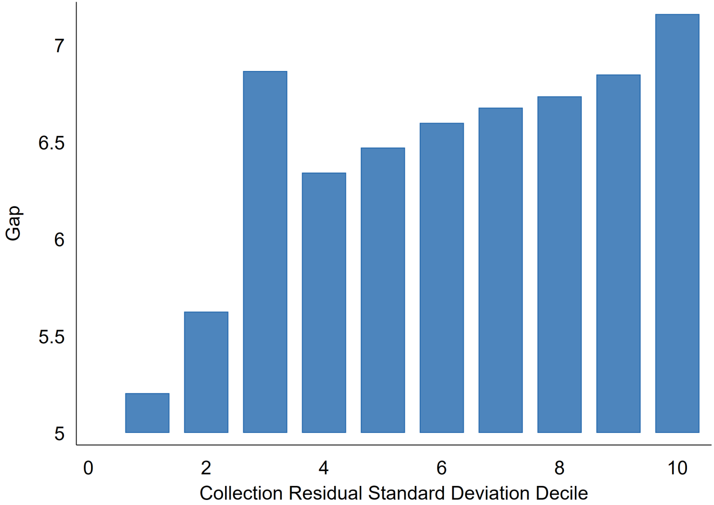


Idiosyncratic mean and variance of price appreciation have positive intercept

Search frictions, asset standardization and trading gap (I/II)

- For non-fungible assets, standardization should improve market liquidity because of a lower search delays (see Tsoy (2021)).
- More standardized NFT exhibit less variation in their “private” quality, measured as the residual standard deviation of hedonic regression with collection FE.
- Group NFTs in deciles based on degree of standardization and report corresponding trading gap (i.e., average number of weeks between two repeated sales).

Search frictions, asset standardization and trading gap (II/II)



More standardized collections sell faster

BMN vs Volume (I/II)

- Lovo and Spaenjers (2018) predicts a *positive* relation among volume, art price index and the economy
  - **demand side**:
    - ⋆ more aggressive bidding due to higher emotional dividend
    - ⋆ more bidders
  - **supply side**:
    - ⋆ reserve prices are higher
    - ⋆ fraction of transactions that result from distressed auctions is lower

BMN vs Volume (II/II)