

# 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

# 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
    - idiosyncratic mean and variance of price appreciation have positive intercept
    - more standardized collections sell faster
- Predictability
  - Time-series volatility and valuation ratio
  - Cross-sectional size/masterpiece and reversal effect

# 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 (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  $\beta_k$  estimates provide information on the determinants of NFT valuations.

## Hedonic regressions (II/II)

- Full sample: time, currency, collection and repeat sale dummies
- Creator sample: add creator characteristics
  - artist royalty fees
  - artist dummy
- 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

### Bored Ape Yacht Club #3284



#### Traits: 5/7

**Eyes:** Robot

**Background:** Yellow

**Fur:** Cream

**Mouth:** Bored Unshaven Dagger

**Clothes:** Rainbow Suspenders

**Hat:** <null>

**Earring:** <null>

# 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.
- Each trait has different possible features or attributes (e.g., Eyes: Robot).

# Trait ratio

- The trait ratio is the number of non-null traits as a fraction of the number of available traits in a collection.
- In the example of the BAYC # 3284 the trait ratio is  $5/7$ .

## 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

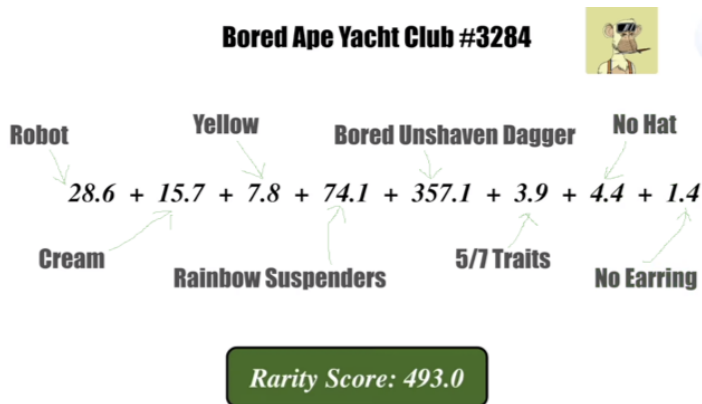
$$\frac{350}{10\,000} = 3.5\%$$

*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: 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
<i>Creator Characteristics</i>			
$\log(\text{Fee} + 1)$	N	0.050 (97.43)	N
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.

# 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 (35.04)	0.024 (32.40)	0.026 (35.89)	0.027 (37.14)	0.026 (36.24)	0.026 (35.98)
<i>NFT Characteristics</i>						
Trait Ratio	N	-0.451 (-114.17)	N	N	N	N
Rarity 1	N	N	0.184 (195.49)	N	N	N
Rarity 2	N	N	N	0.184 (195.49)	N	N
Rarity 3	N	N	N	N	0.171 (161.94)	N
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 <sup>2</sup>	0.8297	0.8395	0.8380	0.8378	0.8378	0.8379

## 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:

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

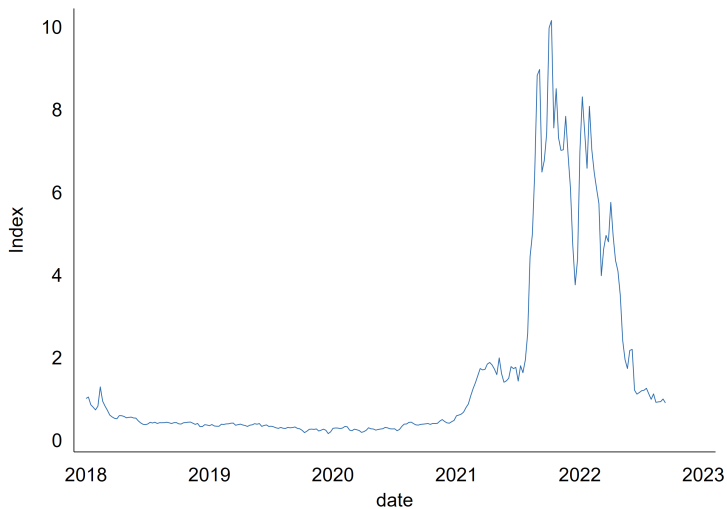
# Why RSR?

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

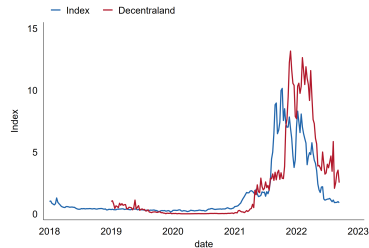
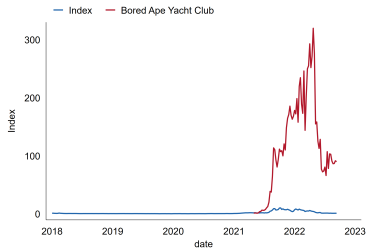
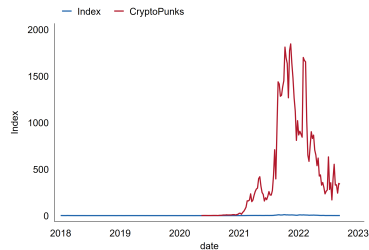
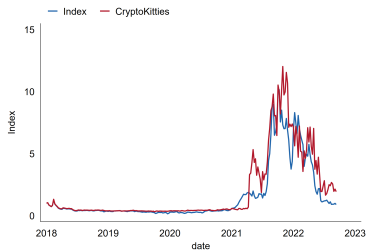
# Explanatory Power

	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



# Some Collection Indices



## Summary Statistics

<b>Panel A</b>	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
<b>Panel B</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%	

# Exposures of NFT Market

# Cryptocurrency Market

	(1)	(2)
	$R^{NFT} - R^f$	$R^{NFT} - R^f$
CMKTRF	0.497*** (6.12)	0.502*** (6.15)
CSIZE		0.106 (0.87)
CMOM		0.067 (0.51)
$\alpha$	0.007 (0.86)	0.06 (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)
$\alpha$	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

Market segmentation and testable predictions

# 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  $i$ :  $S_i^{max} = N_{ic}^{max} / \sum_c N_{ic}$
  - 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

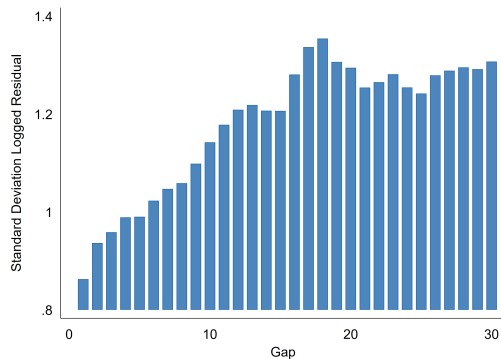
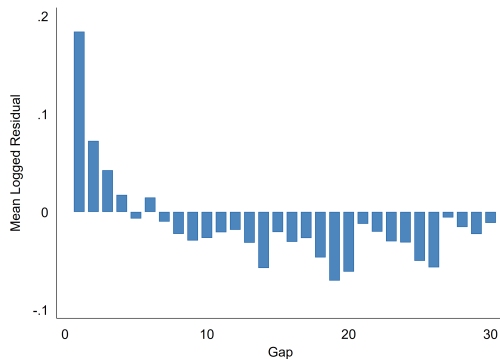
Based on repeat sales regressions.

	<i>r</i>	<i>r</i>	<i>r</i>	<i>r</i>
$\log(\#buy)$	0.022*** (162.31)	0.004*** (23.18)	0.010*** (51.89)	0.011*** (53.63)
<i>FirstSale</i>		0.158*** (127.34)	0.246*** (165.52)	0.245*** (164.91)
$\log(avggap)$			-0.062*** (-107.33)	-0.059*** (-97.00)
<i>Ratio<sup>diff</sup></i>				-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

## 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.

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

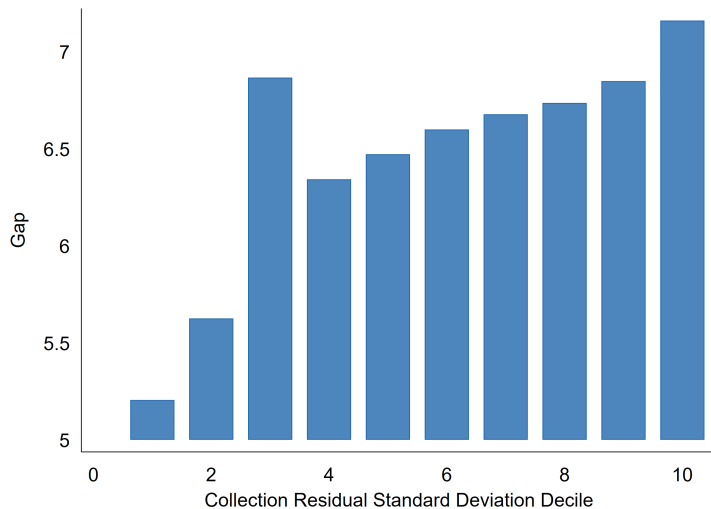


Idiosyncratic mean and variance of price appreciation have positive intercept

## 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)

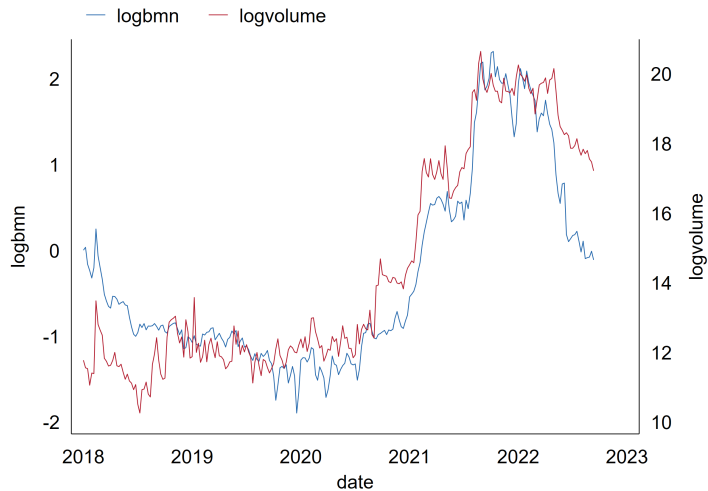


More standardized collections sell faster

# 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)



# Time-Series Return Predictability

# Candidates

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

# Volatility

	+1	+2	+3	+4	+5	+6	+7	+8
<i>Vol</i>	-0.045 (-0.590)	-0.119 (-0.875)	-0.197 (-1.170)	-0.287 (-1.510)	-0.368* (-1.690)	-0.483* (-1.906)	-0.606** (-2.113)	-0.739** (-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* → 14.8% decrease in cumulative NFT market return at eight-week horizon

# Valuation Ratio

<b>Panel A</b>	+1	+2	+3	+4	+5	+6	+7	+8
$\log (Index / Trans)$	-0.061*** (-3.698)	-0.120*** (-3.589)	-0.164*** (-3.272)	-0.203*** (-3.350)	-0.239*** (-3.591)	-0.271*** (-3.693)	-0.309*** (-3.846)	-0.339*** (-3.772)
R-squared	0.071	0.124	0.152	0.177	0.206	0.228	0.255	0.269
<b>Panel B</b>	+1	+2	+3	+4	+5	+6	+7	+8
$\log (Index / Trans)$	-0.066*** (-4.156)	-0.122*** (-3.701)	-0.162*** (-3.301)	-0.196*** (-3.361)	-0.232*** (-3.697)	-0.262*** (-3.763)	-0.289*** (-3.647)	-0.307*** (-3.460)
<i>Vol</i>	-0.031 (-0.435)	-0.101 (-0.763)	-0.176 (-1.043)	-0.258 (-1.286)	-0.330 (-1.385)	-0.440 (-1.573)	-0.561* (-1.771)	-0.697** (-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  $\log (Index / Trans)$   $\rightarrow$  19.1% decrease in cumulative NFT market return at five-week horizon

# Attention

<b>Panel A</b>	+1	+2	+3	+4	+5	+6	+7	+8
<i>Google<sup>NFT</sup></i>	0.023 (1.558)	0.019 (0.688)	0.010 (0.247)	0.016 (0.353)	0.018 (0.346)	0.017 (0.288)	0.029 (0.464)	0.021 (0.289)
R-squared	0.010	0.003	0.001	0.001	0.001	0.001	0.002	0.001
<b>Panel B</b>	+1	+2	+3	+4	+5	+6	+7	+8
<i>Google<sup>Crypto</sup></i>	0.013 (0.830)	0.005 (0.177)	0.016 (0.380)	0.022 (0.375)	0.032 (0.410)	0.043 (0.457)	0.032 (0.305)	0.018 (0.155)
R-squared	0.004	0.000	0.002	0.003	0.005	0.008	0.004	0.001
<b>Panel C</b>	+1	+2	+3	+4	+5	+6	+7	+8
<i>Google<sup>Bitcoin</sup></i>	-0.002 (-0.139)	0.001 (0.031)	0.008 (0.197)	0.018 (0.304)	0.041 (0.581)	0.057 (0.689)	0.072 (0.756)	0.076 (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 (-0.247)	-0.188 (-0.614)	-0.273 (-0.683)	-0.346 (-0.718)	-0.284 (-0.554)	-0.152 (-0.287)	-0.081 (-0.158)	-0.122 (-0.240)
R-squared	0.000	0.005	0.007	0.008	0.004	0.001	0.000	0.001

# Volume

<b>Panel A</b>	+1	+2	+3	+4	+5	+6	+7	+8
<i>Volume</i>	0.054*** (2.901)	0.072** (2.040)	0.090* (1.727)	0.098 (1.455)	0.081 (1.019)	0.080 (0.903)	0.088 (0.900)	0.076 (0.727)
R-squared	0.041	0.033	0.035	0.031	0.017	0.015	0.015	0.010
<b>Panel B</b>	+1	+2	+3	+4	+5	+6	+7	+8
<i>Volume</i>	0.039* (1.863)	0.042 (1.216)	0.049 (0.993)	0.044 (0.734)	0.015 (0.210)	0.002 (0.024)	-0.003 (-0.038)	-0.025 (-0.308)
<i>log (Index/Trans)</i>	-0.059*** (-3.833)	-0.115*** (-3.579)	-0.153*** (-3.248)	-0.189*** (-3.333)	-0.230*** (-3.724)	-0.261*** (-3.823)	-0.289*** (-3.723)	-0.312*** (-3.540)
<i>Vol</i>	-0.013 (-0.177)	-0.081 (-0.602)	-0.153 (-0.904)	-0.237 (-1.203)	-0.323 (-1.392)	-0.439 (-1.605)	-0.562* (-1.810)	-0.708** (-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*** (-14.092)	-0.001*** (-14.348)	-0.001 (-0.834)
	Bored Ape	Sup Ducks	Decentraland
$(t' - t) \ln P$	-0.002* (-1.804)	-0.011*** (-3.327)	-0.013*** (-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

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

## Serial Dependence

	Full Sample	CryptoKitties	CryptoPunks
$(t' - t) r_{i,t}$	-0.013*** (-8.062)	-0.004*** (-8.774)	-0.089*** (-2.760)
	Bored Ape	Sup Ducks	Decentraland
$(t' - t) r_{i,t}$	-0.016*** (-3.453)	-0.017** (-2.821)	-0.012*** (-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)

Conclusion

# Conclusion

- Construct indices for the NFT market
- Overall summary statistics
- Predictions in terms of assets, market and investors
- Time-series and cross-sectional predictability

# 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  $k$ :

$$RS = \sum_{k=1}^{N_T} \frac{N_C}{N_{T_{kj}}} \quad (1)$$

# 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:  $\sigma(NC / N_{T_{kj}})$

▶ back to presentation

# Exposures of NFT Market

## Traditional Asset Market

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Gold	0.906			
	(1.325)			
BBG Commodity		1.861***		
		(2.895)		
Dollar			-1.821	
			(-1.077)	
Carry				2.707
				(1.583)
$\alpha$	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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▶ back to presentation

# NFT Coins

	$R^{Coins} - R^f$		$R^{Coins} - R^f$			
$R^{NFT} - R^f$	0.333*** (5.408)		0.146** (2.105)			
CMKTRF			0.737*** (6.250)			
$\alpha$	0.017 (1.419)		0.019* (1.729)			
R-squared	0.125		0.263			
$R^{Coins} - R^f$	+1	+2	+3	+4	+5	+6
$R^{NFT} - R^f$	0.229*** (3.077)	0.330** (2.553)	0.328 (1.585)	0.311 (1.239)	0.297 (1.064)	0.391 (1.042)
CMKTRF	-0.239 (-1.625)	-0.012 (-0.053)	0.144 (0.404)	0.406 (1.139)	0.743 (1.359)	0.810 (1.200)
R-squared	0.042	0.042	0.028	0.028	0.031	0.027