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Dynamic Double Auctions: An Analysis of Secondary Sneaker Market and its Future as an NFT Marketplace

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Dynamic Double Auctions:

An Analysis of Secondary Sneaker Market and its Future as an NFT Marketplace

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By

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Abstract

A theoretical analysis of a dynamic double auction over time shows that greater market density can result in more aggressive trading strategies from buyers and sellers. In addition, my model suggests a fast price discovery period initially, with impatient investors having a more aggressive approach. I confirm these results using resale sneaker data from the StockX website for five deadstock sneakers. I find that market density is positively correlated with bid prices, and the bid-ask spread decreases over time during the price discovery period. However, the results also indicate that sellers price in additional transaction costs and lags in their asking prices. This leads them to increase their ask prices even with more sellers in the market. Hence, an NFT marketplace can improve efficiency and welfare significantly by introducing a faster and cheaper trading experience. The dynamic double auction model fits well in the contents of the NFT marketplace.

Keywords: Sneaker, Auctions, NFT

JEL Codes: B21, D44, B26

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Contents

1 Introduction

> NFTs have the potential to radically change the book industry. We are offering a unique NFT package to test the waters and see what works best to create value for the buyer. This could provide a new revenue stream for every book.
> – Robert Pozen, Senior Lecturer, MIT Sloan

On October 1, 2021, senior lecturer Robert Pozen from MIT Sloan opened an Non-fungible token (NFT) auction for his book *Extreme Productivity: Boost Your Results, Reduce Your Hours* on the OpenSea platform. The auction winner will receive a 3D NFT of a new cover and a new preface, together with Pozen's digital signature. In addition, the winner will receive an hour of free consulting with Pozen and a free seat in his related upcoming MIT Sloan Executive Education class, Maximizing Your Personal Productivity: How to Become an Efficient and Effective Executive (MIT Sloan Office of Media Relations, 2021). This example represents one of the asset-backed NFT revolution in academia. NFTs have been around for a while; however, 2021 has seen several high-profile sales, including the $69.3 million Christie's sale of the NFT associated with Everyday: the First 5000 Days — a digital artwork by the US artist Beeple. So what is an NFT? In short, NFTs are tokens that we can use to represent ownership of unique items. They let us tokenize things like art, collectibles, even real estate (ethereum.org, 2021). Recently, LuxFi launched the first asset-backed NFT marketplace for luxury products. To link NFTs with physical assets, they used a product fingerprint technology so that users can scan the QR code/NFC tag of the items and view the history of each item.

Inspired by cutting-edge technology, I am interested in understanding investor behaviors in the NFT marketplace. With personal interests in collectible sneakers, this research focuses on the secondary sneaker market and its extension to the NFT marketplace. Investors in secondary sneaker market often experience high transaction costs and shipping delay. An sneaker-baked NFT marketplace can help solve those issues. Since the NFT sneaker marketplace is limited in its users, I conducted a theoretical analysis of the authentic dead-stock sneakers market and its comparison with NFT marketplace. The baseline model and regres-

sion results suggest that with a higher market density, buyers and sellers would react more aggressively. In addition, we would expect a quick price discovery period in the beginning as impatient buyers and sellers would have a more aggressive bidding strategies. However, the transaction costs and shipping delay would create inefficiency in the market and a loss in welfare for both buyers and sellers. To give more context, the buyer needs to pay an additional 6% processing fee, including processing and verification service, $14.95 flat shipping cost, and sales taxes depending on buyer and seller location. The seller also needs to pay 10% of transaction fees and 3% of the payment processing fee from the selling price. In addition, the transaction period usually takes around nine days as the seller has two days to ship, and StockX needs to verify the product seller sends. Hence, an introduction of an NFT marketplace would create a faster and cheaper way of trading sneakers.

Research has shown the secondary sneaker industry is worth $2 billion in North American and is expected to grow to $30 billion by 2030 (Ciment, S., 2021). Especially in the recent decade, people not only wear sneakers, but also value them as a part of the culture. Celebrities such as Travis Scott and Kanye West have collaborated with large shoe brands like Nike and Adidas to release their signature shoes. Currently, the Jordan 1 Retro High Travis Scott sneaker fetches an average sale price of $1,748 – a 940% premium over its retail price of $175, while Kanye West's signature sneaker Adidas Yeezy Boost 750 sells premium over for an average of $1,592 —- a 300% the retail price of $350. The rise of "sneaker culture" is not just a a US phenomenon, but rather a global phenomenon with the worldwide sneaker market valued at over $55 billion USD. However, traders in the secondary market often face high costs of transactions and slow delivery when trading sneakers.[1] When I overheard blockchain and NFT technology during my internship with Citigroup, it inspired me to investigate investors' behaviors in the sneaker market and its potential extension to the NFT marketplace.

The current paper models the secondary sneaker market using a dynamic double auction model with multiple players. I use the model to help interpret data collected from the StockX

[1]Following the trend, my cousin and I used to trade secondary sneakers and made a slight profit from the high market premium.

website for five specific deadstock sneakers, which are exclusive in supply and are sold with a premium in the secondary resale markets, over a 50-day period.

The remaining sections of the paper are as follows: section 2 introduces relevant literature. Section 3 describes the baseline to dynamic double auction models. Section 4 introduces the data collection process and provides a summary of the data. Section 5 provides the regression results of bid-ask spread and individual bid/ask prices specification with analysis. Lastly, Section 6 introduces the dynamic double auction model in the real-life setting with discussions of the NFT marketplace.

2 Literature Review

My research is related to the bid-ask spread literature in a resale market. Much of this literature focuses on the components of the bid-ask spread, such as return variance, the ratio of the number of sales over bids, product stock prices, volumes, etc. Watts (2019) examines the double auction model with bidders and sellers having different rates of patience over the sneaker auction data. Watts collects data on two Adidas sneakers daily without calling StockX's API (Application Programming Interface). My data collection method is different in that I called the website's API and collected 250 entries twice a day. One of her assumptions is that players will exit the auction market after a transaction is done. Based on her baseline model, I will incorporate a resale value function and cost of trade in the double auction model. My research investigates potential extensions from a physical shoe market to an NFT marketplace.

Another piece of literature by Gjerstad and Dickhaut (1995) looks at a double auction model with information processing and strategy choice. Sellers and buyers in the model form a belief based on the observed market data, including accepted asks, accepted bids, and frequency of asks, bids, etc. The model is built based on the spread reduction rule, which constrains the sellers' maximum ask price not exceeding the previously accepted ask price, and vice versa for the buyers. However, in real-life auctions, the spread reduction rule

might not be appropriate. I observe from preliminary data visualization that there is usually a price formation period after the sneaker is released. However, there will be fluctuations in sneaker sell prices in the long run. Inspired by a simple two-player one-period double auction model from Gibbons (1992), I extend the model with multiple players in different periods. Specifically, there is a switch in value function when a buyer becomes a seller and vice versa. Intuitively, a buyer becomes a seller after winning the auction, and a seller becomes a buyer after selling the shoes. In the end, factors such as costs and lags of the transaction are also considered in the model. I detail this model in the next section.

3 Model

To model the bid-ask behavior in the sneaker market, we need to define bidder and seller's objectives and then consider their incentives and behaviors. In this section, we will discuss a simple double auction model with one bidder and seller. Then, based on the double auction model, we will go over a dynamic auction model with bidders and sellers in multiple periods of time.

3.1 Double Auction Model

Following Gibbons (1992), assume there are two players in the sneaker resale market: a buyer and a seller. The buyer draws a private valuation $v_b \sim F_B(v_b)$. Independently, the seller draws a reservation price $v_s \sim F_S(v_s)$. Assume F_B and F_S are distribution functions over the interval [0,1], without loss of generality. The bidder would offer a bidding price p_b and the seller would provide a selling price p_s. If $p_b \geq p_s$, we say a trade occurs and the item will be sold at price $p = (p_b + p_s)/2$ according to Nash bargaining (Watts 2019). If $p_b < p_s$, a trade does not occur. Hence the utility of buyer would follow the following equation

$$u_b = \begin{cases} v_b - p & \text{if } p_b \geq p_s \\ 0 & \text{if } p_b < p_s \end{cases}. \tag{1}$$

Likewise, the utility of seller would be the following function

$$u_s = \begin{cases} p - v_s & \text{if } p_b \geq p_s \\ 0 & \text{if } p_b < p_s \end{cases}. \tag{2}$$

In the Bayesian game, the buyer has a bidding strategy $p_b(v_b)$ whereas seller has a selling strategy $p_s(v_s)$. A pair of strategies $\{p_b(v_b), p_s(v_s)\}$ is a Bayesian Nash equilibrium if the following two conditions hold.

For each v_b in $[0, 1]$, $p_b(v_b)$ solves

$$\max_{p_b} \left[v_b - \frac{p_b + E[p_s(v_s) \mid p_b \geq p_s(v_s)]}{2} \right] \text{Prob}\{p_b \geq p_s(v_s)\}, \tag{3}$$

where $E[p_s(v_s) \mid p_b \geq p_s(v_s)]$ is the expected price the seller will demand, conditional on the ask being less than the buyer's offer of p_b. In addition, for each v_s in $[0, 1]$, $p_s(v_s)$ solves

$$\max_{p_s} \left[\frac{p_s + E[p_b(v_b) \mid p_b(v_b) \geq p_s]}{2} - v_s \right] \text{Prob}\{p_b(v_b) \geq p_s\}, \tag{4}$$

where $E[p_b(v_b) \mid p_b(v_b) \geq p_s]$ is the expected price the buyer will offer, conditional on the offer being greater than the seller's ask of p_s.

In this model, there are many Bayesian Nash equilibria. Figure 1 shows the situation where trade occurs at a single price. Here, for any value x in $[0, 1]$, let the buyer's strategy be to offer x if $v_b \geq x$ and to offer zero otherwise and let the seller's strategy be to demand x if $v_s \leq x$ and to demand one otherwise. Given the buyer and seller's strategies, we know that their strategies complement each other and constitute a Bayes-Nash equilibrium. Therefore, trades occur in all $\{v_b, v_s\}$ pairs in the trade area indicated in Figure 1. Trades do not occur in the shaded area (the area below the 45-degree line corresponds with situations in which $v_s > v_b$ and trade would not occur there either) (Gibbons 1992).

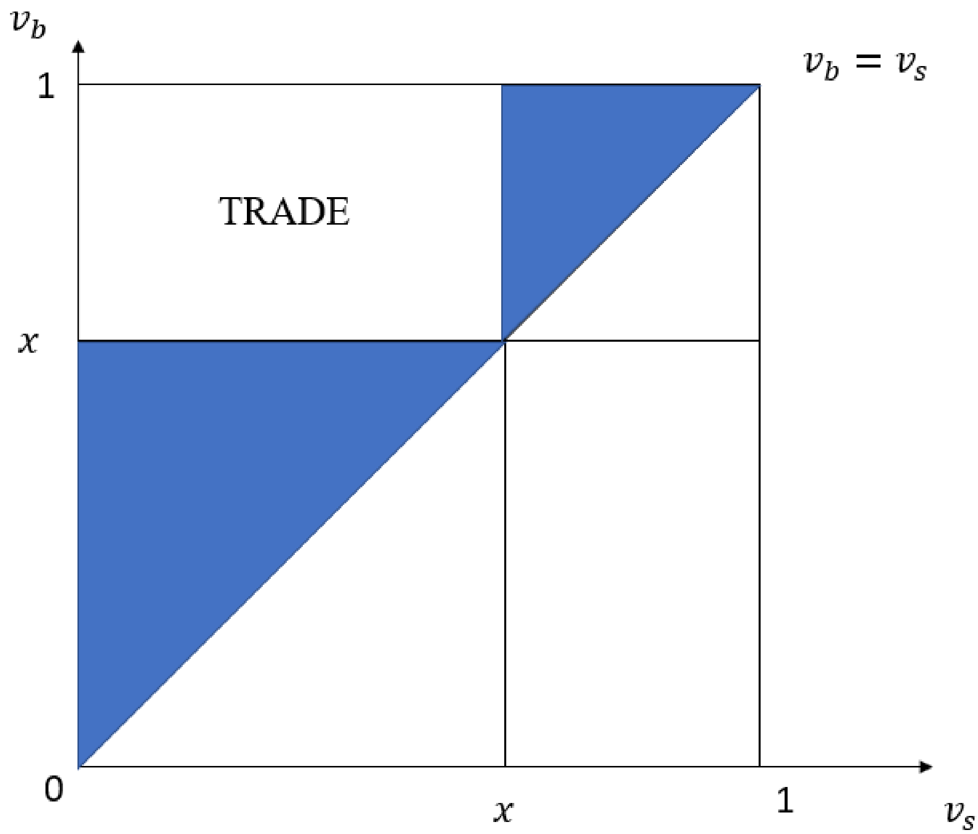


Figure 1: Double Auction Equilibrium

3.2 Static Double Auction with Multiple Players

Extending this framework into static double auction model with multiple players, different from the basis model discussed in the previous section, we have multiple players in this market. We let $M = \{1, 2, \ldots, j, \ldots, m\}$ be a list of sellers and $N = \{1, 2, \ldots, i, \ldots, n\}$ be a list of buyers in this market. Similarly, buyer i draws a private valuation $v_{b_i} \sim F_B(v_{b_i})$. Independently, seller j draws a reservation price $v_{s_j} \sim F_S(v_{s_j})$. We also assume F_B and F_S are distribution functions over the interval [0,1], without loss of generality. Here, we assume that buyer i has the highest bid among buyers and seller j has the lowest ask among sellers.

Hence, for each v_{b_i} in $[0,1]$, $p_{b_i}(v_{b_i})$ solves

$$\max_{p_{b_i}} \text{Prob}(p_{b_i} \geq p_{b_k}\ \forall k \neq i)\ \left[v_{b_i} - \frac{p_{b_i} + E[p_{s_j}(v_{s_j}) \mid p_{b_i} \geq p_{s_j}(v_{s_j})]}{2}\right] \text{Prob}\{p_{b_i} \geq p_{s_j}(v_{s_j})\}, \tag{5}$$

where $E[p_{s_j}(v_{s_j}, \delta_j) \mid p_{b_i} \geq p_{s_j}(v_{s_j})]$ is the expected price the seller j, where $p_{s_j} \leq p_{s_k} \forall k \neq j$, will demand, conditional on the demand being less than the buyer i's offer of p_{b_i}. $\text{Prob}(p_{b_i} \geq p_{b_k}\ \forall k \neq i)$ is when the buyer i wins the auction by beating other buyers' prices. Likewise, for each v_{s_j} in $[0,1]$, $p_{s_j}(v_{s_j})$ solves

$$\max_{p_{s_j}} \text{Prob}(p_{s_j} \leq p_{s_k}\ \forall k \neq j)\ \left[\frac{p_{s_j} + E[p_{b_i}(v_{b_i}) \mid p_{s_j} \geq p_{b_i}(v_{b_i})]}{2} - v_{s_j}\right] \text{Prob}\{p_{s_j} \geq p_{b_i}(v_{b_i})\}, \tag{6}$$

where $E[p_{b_i}(v_{b_i}, \delta_i) \mid p_{s_j} \geq p_{b_i}(v_{b_i})]$ is the expected price the buyer i, where $p_{b_i} \geq p_{b_k} \forall k \neq i$, will offer, conditional on the offer being greater than the seller j's offer of p_{s_j}. $\text{Prob}(p_{s_j} \leq p_{s_k}\ \forall k \neq j)$ is when the seller j wins the auction by beating other sellers' prices.

With multiple players, in order to win the auction, buyer i needs to beat both the seller and other buyers' prices. Hence, we expect to see buyers to be more aggressive than in the single bidder model. Similarly, seller j needs to offer a competitive price that is lower than other seller and satisfies the buyer's valuation. Therefore, sellers in multiple players model are also expected to be more aggressive. Overall, we expect to see that with more buyers and sellers, the bid-ask spread will decrease quicker. We will look at the relationship between bid-ask spread with the thickness of the market in the data section, but first it is important to realize these auctions have dynamic elements as well.

3.3 Dynamic Double Auction Model without Multiple Players

In real life sneaker auction, there are multiple periods where buyers and sellers participate in the market. Hence, we can extend the static double auction model into a dynamic double auction model with multiple players. Note that in this model, we have not added the resale value yet. Similarly, we let $M = \{1, 2, \ldots, j, \ldots, m\}$ be a list of sellers and $N = \{1, 2, \ldots, i, \ldots, n\}$ be a list of buyers in time period $t = 0, 1, 2, \ldots$. In each period, there is a double auction happening. Here, buyer and seller would maximize their value functions in

each period.

In every period, we can define buyer i's value function as

$$V_{b_i}(v_{b_i}, \delta_i) = \text{Prob}(p_{b_i} \geq p_{b_k} \ \forall k \neq i) \ \left[v_{b_i} - \frac{p_{b_i} + E[p_{s_j}(v_{s_j}, \delta_j) \mid p_{b_i} \geq p_{s_j}(v_{s_j})]}{2} + \delta_i \ V_{s_i}(v_{s_i}, \delta_i) \right]$$
$$+ \text{Prob}(p_{b_i} < p_{b_k} \ \forall k \neq i) \ \delta_i \ V_{b_i}(v_{b_i}, \delta_i), \quad (7)$$

where δ_i represents the discounted rate of buyer i. The rest of the equation is similar to the static case. The difference is that when buyer i wins, the buyer will become a seller. Hence, we add $\delta_i \ V_{s_i}(v_{s_i}, \delta_i)$ into the utility when the buyer wins and the next period becomes a potential seller. If the buyer loses, it will still remain a bidder in the next period. For seller j, we have the value function as

$$V_{s_j}(v_{s_j}, \delta_j) = \text{Prob}(p_{s_j} \leq p_{s_k} \ \forall k \neq j) \ \left[\frac{p_{s_j} + E[p_{b_i}(v_{b_i}, \delta_i) \mid p_{s_j} \geq p_{b_i}(v_{b_i})]}{2} - v_{s_j} + \delta_j \ V_{b_j}(v_{b_j}, \delta_j) \right]$$
$$+ \text{Prob}(p_{s_j} > p_{s_k} \ \forall k \neq j) \ \delta_j \ V_{s_j}(v_{s_j}, \delta_j). \quad (8)$$

where δ_j represents the discounted rate of seller j. When seller j sells a pair of shoes, the seller will become a buyer. Hence, we add $\delta_j \ p_{b_j}(v_{b_j}, \delta_j)$ into the utility when the seller wins. If the seller fails to sell the shoes, the person will still remain a seller in the next period.

Hence, from the value functions, if a buyer is impatient and has a high discount rate, the buyer would bid more aggressively at the beginning than other buyers whose discounted rates are lower. The same applies to the seller, where higher discount rate means a seller is impatient and accepts a lower asking price. Overall, we expect to see the bid prices go up if buyers are patient and the ask prices increase if sellers are patient. Intuitively, with more sellers and buyers in the market, one would have a more aggressive strategy.

4 Data

I use the model to guide interpretation of data collected from StockX, the primary data source for this paper. The data was collected from the StockX website[2] over 50 days, specifically from March 5, 2022, until April 23, 2022. To provide some background, StockX is one of the sneaker marketplaces that facilitate auctions between sellers and buyers and collect transaction and payment fees. StockX will authenticate the seller's items and then ship them to buyers. If items are determined to be counterfeit, the transaction will be voided; the counterfeit items returned to the seller and the buyer is refunded (Wikimedia Foundation, 2021). One of the highlights of the website is that it surpassed eBay in total sneaker transactions in 2017. Hence, StockX is an excellent resource for collecting authenticated sneakers' bid, ask, and sale data.

StockX does not provide a publicly available dataset. Hence, I deploy StockX internal APIs to extract daily ask, bid, and sale information on sneaker transactions. Daily sales, bid, and ask data were collected on five sneakers; namely, Jordan 6 Retro UNC White (1), Nike SB Dunk High Supreme By Any Means Brazil (2), Nike SB Dunk High Supreme By Any Means Navy (3), Nike SB Dunk High Supreme By Any Means Black (4), and Nike SB Dunk High Pass ∼ Port Work Boots (5). The data was collected twice a day, once at 5 a.m. and once at 5 p.m. The python extraction code can be found in Appendix A. The five selected sneakers are not associated with specific celebrities to avoid celebrity news shocks. Here Nike SB Dunk High Supreme By Any Means Black, Nike SB Dunk High Supreme By Any Means Brazil, and Nike SB Dunk High Supreme By Any Means Navy were released on March 3, 2022. Jordan 6 Retro UNC White and Nike SB Dunk High Pass ∼ Port Work Boots were released on March 5, 2022. Figure 2 shows images of fives shoes.

The raw data from StockX consists of *chainId* (identifies buyer or seller's ID), prices, date the bid or ask price was created, shoe size, and *skuUuid* (identifies shoe' ID). Table 1 shows a summary statistics of for all five shoes. The number of unique buyers and sellers is calculated based on the number of unique *chainId* in the dataset. They represent the number

[2] https://stockx.com/

	(1)	(2)	(3)	(4)	(5)
Release Date	03/05/2022	03/03/2022	03/03/2022	03/03/2022	03/05/2022
Number of Unique Buyers	2477	1293	1522	1875	1369
Number of Unique Sellers	6009	1694	2394	2777	2285
Average Ask Duration	10 days 16 hrs	8 days 08	8 days	7 days 05	20 days 02
Average Bid Duration	15 days 23 hrs	8 days 20	8 days 11	9 days 20	7 days 12
Max Ask Duration	32 days 18 hrs	26 days 05	30 days 01	28 days 22	44 days 23
Max Bid Duration	43 days 8 hrs	48 days 20	50 days 03	45 days 08	43 days 05
SD Ask Duration	12 days 4 hrs	11 days 02	11 days 01	10 days 11	16 days 06
SD Bid Duration	15 days 3 hrs	10 days 14	12 days 02	12 days 22	10 days 23
Number of Sales	12076	1172	1867	2459	1669

Table 1: Data Collection Summary

of unique buyers and sellers of a specific shoe size of a specific shoe. The average ask/bid duration, max ask/bid duration, and standard deviation ask/bid duration are calculated by tracking the *chainId* in the dataset. Average bid/ask duration records the average bid/ask appearing in the market. The maximum bid/ask duration represents the maximum time one ask/bid stays on the market. Lastly, SD bid/ask duration represents the standard deviation of the time of all bid/ask pieces existing on the market. From Table 1, there are more sellers than buyers for all five shoes. Except for Nike SB Dunk High Pass $\sim$ Port Work Boots, the average bid duration for the other four shoes are higher than the average ask duration. The same follows for the maximum ask/bid duration. On average, it means that the bids stay longer than asks on the market. This suggests that buyers are more patient than sellers, which makes sense given that the number of buyers is smaller than the number of sellers. Buyers tend to have fewer competitors than sellers. Hence, on average, buyers bid less aggressively than sellers. We will define the term market thickness at the end of the section. Further, the standard deviations of ask and bid duration are close to each other. The standard deviation of ask duration is slightly lower than the standard deviation of bid duration. This reflects that sellers have similar valuations of shoes which causes the standard deviation of ask duration to be lower. With sellers facing more competition than buyers, it is faster for sellers to find the competitive pricing and strategy to sell their shoes. However, for buyers, their bidding strategies differ, which causes the standard deviation of bid duration to be higher. With buyers facing less competition, it is slower for buyers to discover the shoes' competitive strategy and equilibrium evaluation.

Figure 3 shows the median ask/bid/sale prices by shoe size over time. The median is chosen here rather than average to avoid the effect of extreme outliers. Overall, the median sale prices have a downward trend across all shoe sizes. It is unclear how the bid-ask spread changes over time from the graph. However, the median sale prices are closely aligned with the median asking prices. The median bid prices across all shoe sizes have a slight downward trend. We see from the graph that sellers seem to have a more structured asking strategy than buyers as sellers tend to have similar valuations. It might be because the market size of the sellers is larger than the market size of the buyers. Hence, competition from sellers

(a) Nike SB Dunk High Supreme By Any Means Black, Brazil, and Navy

(b) Jordan 6 Retro UNC White

(c) Nike SB Dunk High Pass ∼ Port Work Boots

Figure 2: Sneakers Image

leads to a more structured valuation and selling strategies, which reflects similar story from data summary table. In addition, we can observe that the median bid prices are higher in the beginning. It suggests that impatient buyers might exit the markets quickly. Figure 4 shows the standard deviation of ask/bid/sale prices by shoe size over time. Shoe sizes 7, 10, and 16 have more variation than other shoes regarding their ask and bid prices. It might be because of fewer investors in those markets. Hence, it takes more time for investors to find the best strategy. Overall, Figure 3 and Figure 4 suggest the bid, ask, and sale behaviors vary across different shoe sizes. Appendix B shows visualizations of other shoes. Overall, there are fewer investors in the raw shoe sizes. Hence the standard deviation of those shoes is more prominent than other shoes. The patience story also holds for other shoes. Market thickness is defined as number of buyers and sellers for a given shoe market. We will examine

Figure 3: Jordan 6 Retro UNC White Median Ask, Bid, and Sale Prices by Size

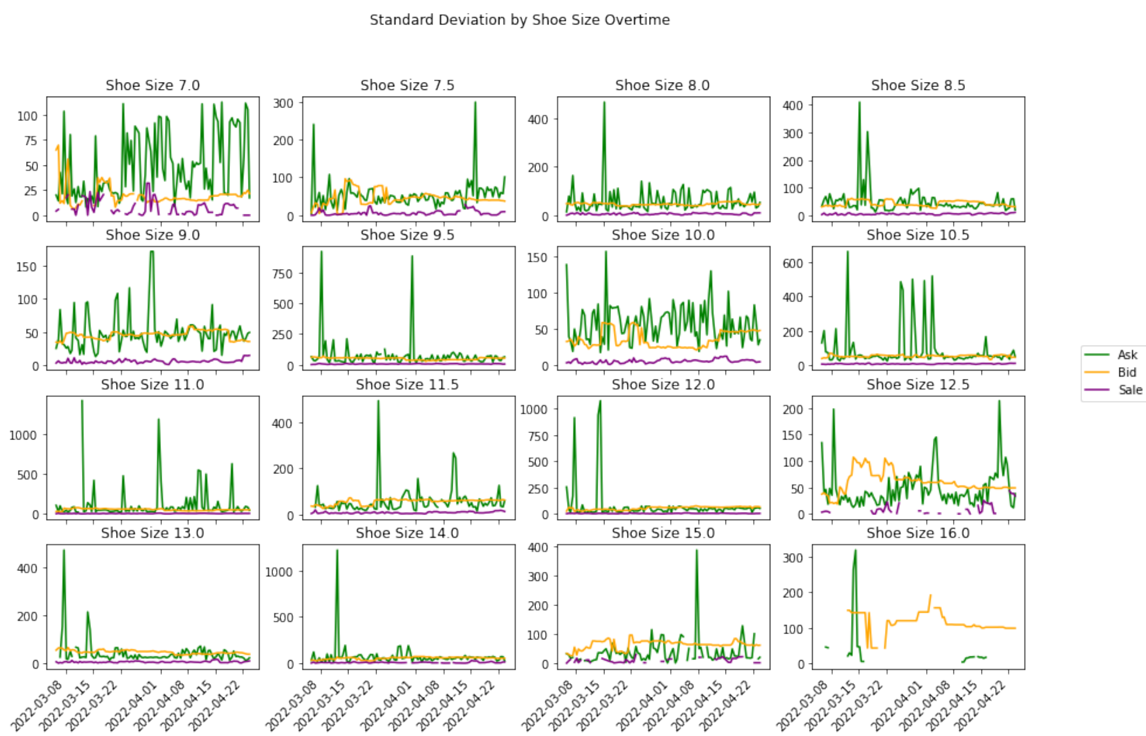


Figure 4: Jordan 6 Retro UNC White Standard Deviation Ask, Bid, and Sale Prices by Size

the effect of market thickness to bid/ask spread and individual bid/ask prices.

5 Empirical Model & Results

We examine the bid-ask spread over time and the effect of market thickness predicted in section 3. Formally, our model is presented as

$$Spread_{ist} = \beta_0 + \beta_1(Time_t) + \beta_2(Time_t)^2 + \beta_3(Time_t)^3 + \beta_4(B_{ist}) + \beta_4(S_{ist}) + \gamma_i + \lambda_s + \epsilon_{ist}. \quad (9)$$

In Equation 9, $Spread_t$ represents the minimum ask minus the maximum bid; this variable is for a given shoe size (i) for a specific shoe (s) at a given time or date (t). On the right-hand side, $Time_t$ represents the time or the number of days since the shoe's release. To reiterate, Nike SB Dunk High Supreme By Any Means Black, Nike SB Dunk High Supreme By Any Means Brazil, and Nike SB Dunk High Supreme By Any Means Navy were released on March 3, 2022. Jordan 6 Retro UNC White and Nike SB Dunk High Pass $\sim$ Port Work Boots were released on March 5, 2022. B_{ist} accounts for the number of unique buyers for a specific size of a specific shoe. Similarly, S_{ist} represents the number of unique sellers for a specific size of a specific shoe. Lastly, γ_i represents the fixed effect of a particular shoe size, λ_s is the fixed effect of a particular shoe, and ϵ_{ist} represents robust standard errors. We control shoe/size fixed effects because from Figure 3 and Figure 4, we can see differences in market sizes and standard deviation with respect to different shoe sizes and shoes. We present results with both fixed size/shoe effect and non-fixed size/shoe effect.

Table 2 shows the results of regressions over the bid-ask spread. As discussed in section 3, we would need to control for size and shoe in the model to account for the difference across markets. Overall, bid-ask spread over time is a polynomial function. Figure 5 shows the polynomial function in column three. Formally, we can write predicted spread equation as

$$\hat{Spread}_{ist} = -0.00012(Time_t) + 6 \cdot 10^{-11}(Time_t)^2 - 8.8 \cdot 10^{-18}(Time_t)^3 + 366.3. \quad (10)$$

In Figure 5, note that the x-axis denotes the 50-day data collection period in seconds. Overall, the bid-ask spread goes down in the 50 days, and all coefficients here are significant.

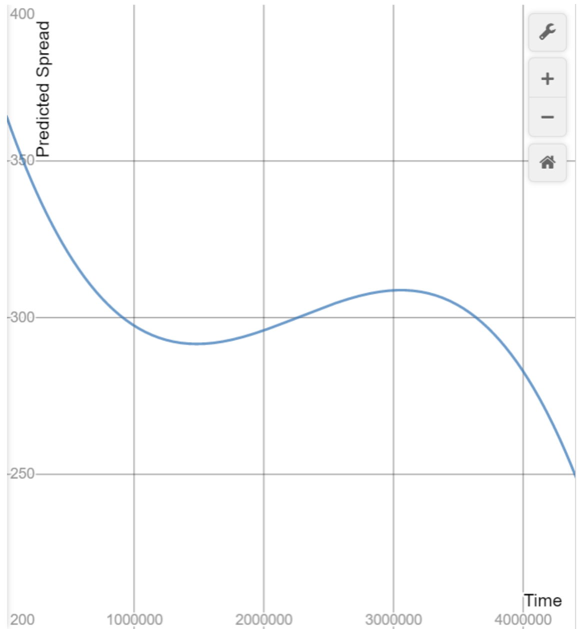
Table 2: Regression over Bid-Ask Spread (Minimum Ask Minus Maximum Bid)

	(1)	(2)	(3)	(4)	(5)
$Time_t$	-0.00000062	0.00000026	-0.00012***	-0.00013***	-0.00010***
	(0.8937)	(0.9955)	(0.0010)	(0.0003)	(0.0025)
$Time_t^2$		9.9e-12	6.0e-11***	6.5e-11***	5.4e-11***
		(0.6717)	(0.0006)	(0.0002)	(0.0016)
$Time_t^3$		-2.9e-18	-8.8e-18***	-9.2e-18***	-7.7e-18***
		(0.3871)	(0.0005)	(0.0002)	(0.0017)
B_{ist}				-20.0***	-19.8***
				(0.0000)	(0.0000)
S_{ist}					-7.71***
					(0.0000)
Shoe FE	No	Yes	Yes	Yes	Yes
Size FE	No	No	Yes	Yes	Yes
Constant	155.5***	31.2	366.3***	459.8***	487.6***
	(0.0000)	(0.3112)	(0.0000)	(0.0000)	(0.0000)
Observations	3401	3401	3401	3401	3401
R^2	0.0000	0.1771	0.5500	0.5672	0.5723

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Predicted Bid-Ask Spread over Time



We can observe a temporary upward trend from day 20 to 40. We expect to see the spread decrease gradually in a polynomial fashion in the future.

In Column 4 and 5, we find negative correlation between number of unique buyers of a particular size of one shoe and the bid-ask spread. It suggests holding everything else constant, with more buyers in the market, the bid-ask spread will decrease. Likewise, we also find bid-ask spread negatively correlates with number of unique sellers of a particular size of one shoe. With more sellers in the market, it will also decrease the bid-ask spread overtime. Hence, buyers and sellers would bid more aggressively when there are more competition in the market because they need to increase their probability to win against other players as our model in section 3 suggested.

Further, we examine factors for individual bid/ask prices. We present results with both fixed shoe/size effect and non-fixed shoe/size effect. Formally, our model is presented as

$$\begin{aligned} Y_{istj} = \beta_0 + \beta_1(Time_t) + \beta_2(Time_t)^2 + \beta_3(Time_t)^3 + \\ \beta_4(maxbid_{ist}) + \beta_5(minask_{ist}) + \beta_6(B_{ist}) + \beta_7(S_{ist}) + \gamma_i + \lambda_s + \epsilon_{ist}, \quad (11) \end{aligned}$$

where Y_{istj} has two possibilities: (a) buyers' bidding prices and (b) sellers' asking prices.

Similarly, all of these variables are for given shoe size (i) with a specific shoe (s) at a given time or date (t). j refers to if the price is a bidding price or a asking price. We keep time as a polynomial in this model. Intuitively, when a buyer and a seller enter the market, they would refer to the maximum bid prices or the minimum ask prices to determine their prices in the market. Hence, $maxbid_{ist}$ and $minask_{ist}$ are added in the model. From the model discussed in section 3, market thickness also plays a major role for buyers and sellers in determining their strategies. Therefore, B_{ist} and S_{ist} from Equation 9 are added here to measure market thickness. For buyers, we expect to see a positive correlation between bid prices and the number of unique buyers in the market. In addition, with more sellers in the market, we expect buyers to bid less aggressively. Sellers are expected to increase their ask prices if there are more buyers in the market. However, with more sellers in the market, we expect to see the ask prices go down. Similarly, we add γ_i to account for the fixed effect of a particular shoe size, λ_s to control the fixed effect of a particular shoe, and ϵ_{ist} to represent robust standard errors. We transfer dependent variable Y_{istj} into log form for ask prices to transform the distribution to a more normally-shaped bell curve and reduce the skewness of our original data because there are abnormal ask prices, especially in the early stage of the auctions. There are much fewer abnormal bid prices in our dataset. Hence, we decide not to transform bid prices.

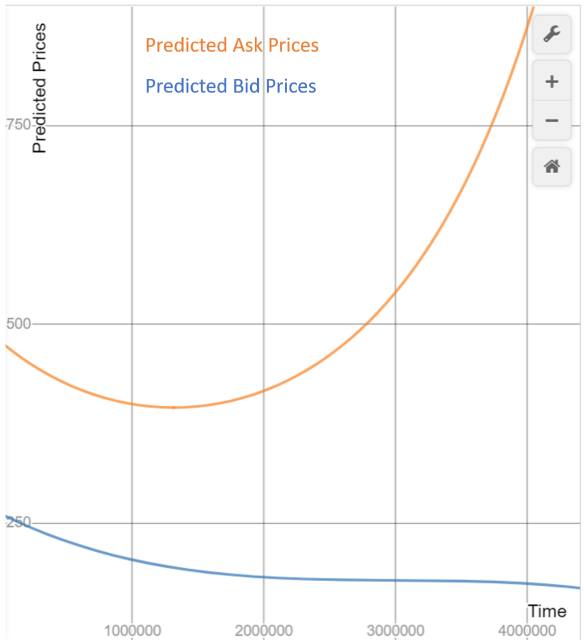
Table 3 shows the regression over log ask prices and Table 4 shows the regression over bid prices. First, from Column 1, we still observe the log ask prices and bid prices are polynomial functions of time. Formally, we write

$$\hat{Y_{ist1}} = -0.000082x \;+\; 2.7 \cdot 10^{-11}x^2 - 3.0 \cdot 10^{-18}x^3 + 261.7 \tag{12}$$

$$\ln \hat{Y_{ist2}} \;=\; -0.00000029x + 1.1 \cdot 10^{-13}x^2 - 1.4 \cdot 10^{-20} + 6.17, \tag{13}$$

where $\hat{Y_{ist1}}$ denotes the predicted ask prices and $\hat{Y_{ist2}}$ denotes the predicted bid prices for given shoe size (i) with a specific shoe (s) at a given time or date (t). We control for shoe and size effects here for both equations. Figure 6 shows plots for both functions through the data collection period. The predicted ask prices have an upward trend in the graph whereas the predicted bid prices have a slight downward trend over time. Although Equation 10 predicts bid-ask spread (minimum ask price minus maximum bid price) would decrease, by looking

Figure 6: Predicted Bid/Ask Prices over Time



at individual bid/ask prices, we expect to see patient buyers and sellers in the market and increase the gap between individual bid and ask prices. It might also be because StockX requires comprehensive commission/delivery fees on top of the sales prices. Hence, with the same valuation, prices tend to increase to cover the additional costs of transaction. We will further discuss the transaction costs in Section 6.

Next, from Columns (2) to (5) in Table 3, we see maximum bid positively correlates with log ask prices. It makes sense because sellers can maximize their utility given higher maximum bid prices by increasing their ask prices. There is also a positive correlation between log ask prices, and minimum ask prices. Sellers are expected to raise their ask prices when the minimum ask price increases. The changes in sellers' asking prices indicate that sellers change their asking strategies based on the market condition. After controlling shoe/size fixed effects in Column (5) in Table 3, the coefficient of B_{ist} (number of unique buyers) is not significant, which suggests that sellers' asking strategies might be independent of the size of buyers. However, the number of unique sellers has a positive, statistically significant correlation with log ask prices. Our model suggests that more sellers in the

Table 3: Regression over Log Ask Prices

	(1)	(2)	(3)	(4)	(5)
$Time_t$	-0.00000029***	0.00000012***	0.00000011***	-0.000000032***	-0.000000086***
	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)
$Time_t^2$	1.1e-13***	-3.6e-14***	-3.4e-14***	2.1e-14***	3.8e-14***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Time_t^3$	-1.4e-20***	3.6e-21***	3.3e-21***	-3.5e-21***	-5.4e-21***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$maxbid_t$		0.0020***	0.0020***	0.0011***	0.00050***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$minask_t$		0.0017***	0.0017***	0.0016***	0.0016***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
B_{ist}			-0.0015***	-0.00037*	0.00016
			(0.0000)	(0.0517)	(0.5946)
S_{ist}			0.0022***	0.00054***	0.0013***
			(0.0000)	(0.0003)	(0.0000)
Shoe FE	Yes	No	No	Yes	Yes
Size FE	Yes	No	No	No	Yes
Constant	6.17***	4.63***	4.61***	5.01***	5.17***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	65000	65000	65000	65000	65000
R^2	0.4491	0.4830	0.4847	0.5104	0.5193

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression over Bid Prices

	(1)	(2)	(3)	(4)	(5)
$Time_t$	-0.000082***	-0.0000035	-0.0000039*	-0.000016***	-0.000025***
	(0.0000)	(0.1336)	(0.0950)	(0.0000)	(0.0000)
$Time_t^2$	2.7e-11***	1.2e-12	1.4e-12	5.4e-12***	8.5e-12***
	(0.0000)	(0.3151)	(0.2680)	(0.0000)	(0.0000)
$Time_t^3$	-3.0e-18***	-1.0e-19	-1.2e-19	-5.9e-19***	-9.3e-19***
	(0.0000)	(0.5772)	(0.5185)	(0.0017)	(0.0000)
$maxbid_t$		0.73***	0.74***	0.64***	0.56***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$minask_t$		-0.025***	-0.034***	-0.030***	-0.034***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
B_{ist}			-0.48***	-0.40***	-0.56***
			(0.0000)	(0.0000)	(0.0000)
S_{ist}			0.041	-0.053	0.0084
			(0.3314)	(0.2206)	(0.8642)
Shoe FE	Yes	No	No	Yes	Yes
Size FE	Yes	No	No	No	Yes
Constant	261.7***	31.5***	38.6***	78.7***	110.9***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	29198	29198	29198	29198	29198
R^2	0.4665	0.4974	0.4990	0.5037	0.5160

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

market tend to decrease their asking prices, which is different from the regression results. First, it might be because sellers have their shoe valuations independent of the market's size. Hence, with prices increasing, it might be due to sellers with higher valuations coming into the market and raising the prices. Second, as discussed briefly above, we tend to see prices increase over time because of the costs of transactions. We also expect to see lags in transactions over time, which means that the future value functions in the model depreciate during the wait time. Hence, to maintain the same utility level, buyers who become sellers in the next periods tend to increase the asking prices to cover the waiting time and costs of transactions. Section 6 will expand our model to consider such situations.

From Column (2) to (5) in Table 4, we observe a positive correlation between the maximum bid and bid prices over time. It suggests that buyers raise their bid prices to compete with the maximum bid by increasing maximum bid prices. Likewise, there is a negative correlation between minimum ask and bid prices. Buyers would lower their bid prices when observing decreasing minimum ask price to maximize their utilities. Both coefficients are statistically and economically significant. In addition, we observe the bid prices are negatively correlated with the number of unique buyers, which matches the hypothesis of our baseline model discussed in Section 3. With more buyers in the market, meaning more competition, buyers would bid more aggressively. We do not observe statistically significant coefficients for the number of unique sellers in both cases with and without considering shoe/size fixed effects. It makes sense, as recalled in data summary table 1 that in general, there are fewer buyers than sellers for all five shoes. Hence, buyers would pay more attention to the market thickness on the buyers' side than on the sellers' side. In addition, transaction costs and lags of delivery seem not to be a significant problem here, given our regression results. It might also be because the buyers' bidding strategies offset the costs of transactions.

6 StockX Dynamic Double Auction Model & Extension to NFT

As discussed in the last section and the introduction, buyers and sellers need to cover commission fees and experience a significant amount of wait time. Overall, from personal trading experiences and results from regression tables, there is a loss in time and costs of the transaction. Hence, to fit our model to reality, we can define commission (processing fee) as a percentage c_b for the buyer and c_s for the seller. In addition, the model includes a shipping cost as s, which is a constant capture of the flat shipping cost, and sales taxes as τ, which the buyer needs to pay. The seller needs to cover the payment processing fee p as a percentage of the sale price. A factor t is also added over the discounted rate as buyer and seller would experience waiting periods.

Hence, in every period, we can define the updated buyer i's value function as

$$\begin{aligned} V_{b_i}(v_{b_i}, \delta_i) = {} & \text{Prob}(p_{b_i} \geq p_{b_k} \ \forall k \neq i) \\ & \left[v_{b_i} - \frac{p_{b_i} + E[p_{s_j}(v_{s_j}, \delta_j) \mid p_{b_i} \geq p_{s_j}(v_{s_j})]}{2} (1 + c_b + \tau) - s + (\delta_i)^t \, V_{s_i}(v_{s_i}, \delta_i) \right] \\ & + \text{Prob}(p_{b_i} < p_{b_k} \ \forall k \neq i) \ \delta_i \ V_{b_i}(v_{b_i}, \delta_i), \quad (14) \end{aligned}$$

where the buyer needs to wait t periods before becoming a seller. Hence, to maximize the value function, one would expect a buyer to bid on a lower price than before, given the same valuation, to offset the depreciation of value functions during the wait time. In order to maintain the same utility level as before, given the sale price staying the same, buyer needs to lower their valuation of the shoes. One would expect a buyer to place a higher resale price in the future to cover the transaction cost and time because the transaction lags lower the future sales value. Likewise, we can define the updated seller j's value function as

$$\begin{aligned} V_{s_j}(v_{s_j}, \delta_j) = {} & \text{Prob}(p_{s_j} \leq p_{s_k} \ \forall k \neq j) \\ & \left[\frac{p_{s_j} + E[p_{b_i}(v_{b_i}, \delta_i) \mid p_{s_j} \geq p_{b_i}(v_{b_i})]}{2} (1 - c_s - p) - v_{s_j} + (\delta_j)^t \, V_{b_j}(v_{b_j}, \delta_j) \right] \\ & + \text{Prob}(p_{s_j} > p_{s_k} \ \forall k \neq j) \ \delta_j \ V_{s_j}(v_{s_j}, \delta_j), \quad (15) \end{aligned}$$

Figure 7: StockX NFT Vault

where seller needs to wait t periods before becoming a buyer. Hence, the future value function of seller depreciates in the t periods of time. In order to offset the depreciation and loss in profits, the seller would increase the ask price given the same valuations.

From model analysis and regression results, we observe a loss in consumer and production surplus in transactions. Essentially, the loss serves as a commission for the StockX platform. However, for investors who are both sellers and buyers, they would sacrifice almost 30% of profits in one transaction. To maintain the same utility level and valuations, we would see ask prices increase and bid prices decrease over time, which introduces inefficiency and loss of welfare in the physical sneaker trading market. Hence, the introduction of a deadstock sneaker NFT marketplace would enhance efficiency and speed up the price discovery process in auctions. Our hypothesises discussed in Section 3 fits well in the NFT world. To reiterate, we would expect to see with larger number of players in the market, the bid-ask spread would likely decrease as both buyers and sellers would have more competitive strategies. In addition, we would likely to see a fast price discovery time period in the beginning as impatient buyers and sellers would be more aggressive in their bid/ask prices. The NFT

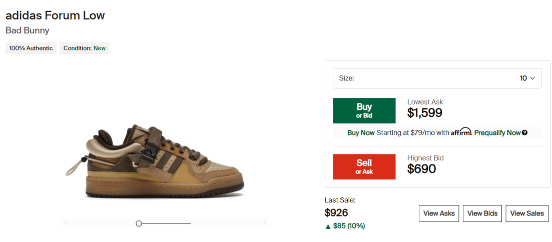
contracts allow a much faster and cheaper transactions which shoes prices can reflect the true valuations from buyers and sellers. By the end of my research, StockX introduced the NFT products in April. Figure 7 shows the mechanism behind the NFT marketplace on StockX. To summarize, StockX Vault NFTs connect coveted physical products with readily tradable digital tokens that track ownership of the physical product. Investors can take possession of the NFT immediately after the transaction is complete, meaning it is the fastest way to flip. Because each Vault NFT is tied to a physical product already stored in the StockX vault, investors no longer has to wait several days before they can resell, and they do not have to pay fees associated with multiple legs of shipping and authentication. Hence, as StockX notes, it is truly a new, faster, cheaper and more efficient trading experience (StockX, 2022).

7 Conclusion

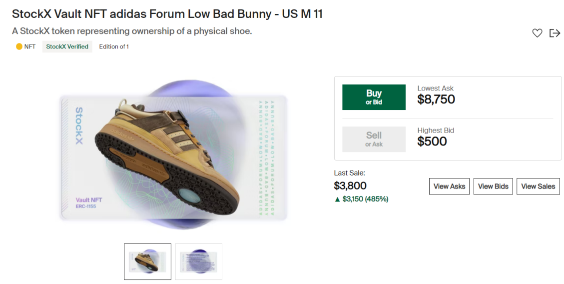
Using resale sneaker data, we analyze the bid-ask spread and individual ask/bid prices. Theoretical analysis suggests that greater market thickness would result in more aggressive trading strategies from buyers and sellers. In addition, we experience a fast price discovery period initially, with impatient investors having a more aggressive approach. These results are tested using resale sneaker data, showing that market density is positively correlated with bid prices and bid-ask spread decreases over time during the price discovery period. However, the result also indicates sellers need to account for costs and lags in transactions. They are likely to increase their ask prices even with more sellers in the market. Hence, by introducing an NFT marketplace, we expect to improve efficiency and welfare significantly. Without considering the cost factors, the dynamic double auction model fits well in the contents of the NFT marketplace.

With StockX introducing NFT products, possible extensions include testing hypotheses of the dynamic double auction model with NFT resale data. The NFT marketplace also challenges investors' valuations of tangible and intangible assets of the same product. For example, in 8a, Adidas Forum Low Bad Bunny size ten shoes have a minimum ask price of $1,590. In Figure 8b, the same shoes but the NFT version has a minimum ask price of

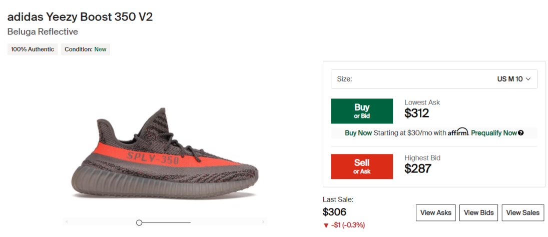
Figure 8: StockX NFT examples



(a) Adidas Forum Low Bad Bunny



(b) Adidas Forum Low Bad Bunny NFT



(c) adidas Yeezy Boost 350 V2

(d) adidas Yeezy Boost 350 V2 NFT

$8,750. In this case, the celebrity-issued sneaker has a much higher price as an NFT than the physical shoes. Figure 8c and Figure 8d are other pairs of examples that shoe the Adidas Yeezy Boost 350 V2 size ten shoe. The minimum ask price of physical shoes is slightly higher than the minimum ask price of NFT shoes. We expect the price difference might account for the costs and lags of transactions. Hence, our model should be able to account for the price differences between the physical and NFT assets. Future research in the NFT marketplace and its relationship to tangible assets could be an extension of this paper.

A Data Extraction Code

```python
import requests
import csv
import json
import random

def extract_data(shoe_name, url, feature):

    user_agents = [
  'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/91.0.4472.124 Safari/537.36',
  'Mozilla/5.0 (X11; Linux x86_64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/92.0.4515.107 Safari/537.36',
  'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/90.0.4430.212 Safari/537.36',
  'Mozilla/5.0 (iPhone; CPU iPhone OS 12_2 like Mac OS X) AppleWebKit/605.1.15 (KHTML, like Gecko) Mobile/15E148',
  'Mozilla/5.0 (Linux; Android 11; SM-G960U) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/89.0.4389.72 Mobile Safari/537.36'
]

    from datetime import datetime
    now = datetime.now()
    # dd/mm/YY H:M:S
    dt_string = now.strftime("%d-%m-%Y %H-%M-%S")
    user_agent = random.choice(user_agents)
    headers = {'User-Agent': user_agent}


    response = requests.get(url, headers = headers)
    ask_data = json.loads(response.text)
    data_file = open('/research/thubbard/Sneaker_data/' + shoe_name + '/' + feature + '/' + dt_string + '.csv', 'w', newline = '')

    # create the csv writer object
```

```
    csv_writer = csv.writer(data_file)

    # Counter variable used for writing
    # headers to the CSV file
    count = 0
    for emp in ask_data:
        if count == 0:

            # Writing headers of CSV file
            header = emp.keys()
            csv_writer.writerow(header)
            count += 1

        # Writing data of CSV file
        csv_writer.writerow(emp.values())

    data_file.close()

shoe_name = "Jordan_6_Retro"
feature = "ask"
url = "https://stockx.com/api/products/a0e50548-e73c-46e8-a5f0-a2e211e5cbc1/activity?limit=100000&sort=createdAt&order=DESC&state=400&currency=USD&country=US"
extract_data(shoe_name, url, feature)

shoe_name = "Jordan_6_Retro"
feature = "bid"
url = "https://stockx.com/api/products/a0e50548-e73c-46e8-a5f0-a2e211e5cbc1/activity?limit=100000&sort=createdAt&order=DESC&state=300&currency=USD&country=US"
extract_data(shoe_name, url, feature)

shoe_name = "Jordan_6_Retro"
feature = "sale"
url = "https://stockx.com/api/products/a0e50548-e73c-46e8-a5f0-a2e211e5cbc1/activity?limit=100000&sort=createdAt&order=DESC&state=480&
```

```
    currency=USD&country=US"
extract_data(shoe_name, url, feature)

Nike_supreme_ask_url = "https://stockx.com/api/products/2ad6c202-4aef
    -4364-97f0-07604d180322/activity?limit=10000&sort=createdAt&order=DESC&
    state=400&currency=USD&country=US"
Nike_supreme_bid_url = "https://stockx.com/api/products/2ad6c202-4aef
    -4364-97f0-07604d180322/activity?limit=10000&sort=createdAt&order=DESC&
    state=300&currency=USD&country=US"
Nike_supreme_sale_url = "https://stockx.com/api/products/2ad6c202-4aef
    -4364-97f0-07604d180322/activity?limit=10000&sort=createdAt&order=DESC&
    state=480&currency=USD&country=US"
shoe_name = "Nike_SB_Dunk_High_Supreme_Black"
feature = "ask"
url = Nike_supreme_ask_url
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Supreme_Black"
feature = "bid"
url = Nike_supreme_bid_url
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Supreme_Black"
feature = "sale"
url = Nike_supreme_sale_url
extract_data(shoe_name, url, feature)


Nike_supreme_ask_url = "https://stockx.com/api/products/410dcddd-c57d-4d17
    -bbeb-7ac3efe3dcca/activity?limit=100000&sort=createdAt&order=DESC&
    state=400&currency=USD&country=US"
Nike_supreme_bid_url = "https://stockx.com/api/products/410dcddd-c57d-4d17
    -bbeb-7ac3efe3dcca/activity?limit=100000&sort=createdAt&order=DESC&
    state=300&currency=USD&country=US"
Nike_supreme_sale_url = "https://stockx.com/api/products/410dcddd-c57d-4
    d17-bbeb-7ac3efe3dcca/activity?limit=100000&sort=createdAt&order=DESC&
```

```
state=480&currency=USD&country=US"
shoe_name = "Nike_SB_Dunk_High_Supreme_Brazil"
feature = "ask"
url = Nike_supreme_ask_url
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Supreme_Brazil"
feature = "bid"
url = Nike_supreme_bid_url
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Supreme_Brazil"
feature = "sale"
url = Nike_supreme_sale_url
extract_data(shoe_name, url, feature)


Nike_supreme_ask_url = "https://stockx.com/api/products/79cde224-297f-4c4a-9bd9-1d075bf810bc/activity?limit=10000&sort=createdAt&order=DESC&state=400&currency=USD&country=US"
Nike_supreme_bid_url = "https://stockx.com/api/products/79cde224-297f-4c4a-9bd9-1d075bf810bc/activity?limit=100000&sort=createdAt&order=DESC&state=300&currency=USD&country=US"
Nike_supreme_sale_url = "https://stockx.com/api/products/79cde224-297f-4c4a-9bd9-1d075bf810bc/activity?limit=100000&sort=createdAt&order=DESC&state=480&currency=USD&country=US"
shoe_name = "Nike_SB_Dunk_High_Supreme_Navy"
feature = "ask"
url = Nike_supreme_ask_url
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Supreme_Navy"
feature = "bid"
url = Nike_supreme_bid_url
extract_data(shoe_name, url, feature)

```

```
shoe_name = "Nike_SB_Dunk_High_Supreme_Navy"
feature = "sale"
url = Nike_supreme_sale_url
extract_data(shoe_name, url, feature)


shoe_name = "Nike_SB_Dunk_High_Pass"
feature = "ask"
url = "https://stockx.com/api/products/5c700c14-1dc4-4ec9-bd5b-8459
    ba8de0db/activity?limit=100000&sort=createdAt&order=DESC&state=400&
    currency=USD&country=US"
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Pass"
feature = "bid"
url = "https://stockx.com/api/products/5c700c14-1dc4-4ec9-bd5b-8459
    ba8de0db/activity?limit=100000&sort=createdAt&order=DESC&state=300&
    currency=USD&country=US"
extract_data(shoe_name, url, feature)

shoe_name = "Nike_SB_Dunk_High_Pass"
feature = "sale"
url = "https://stockx.com/api/products/5c700c14-1dc4-4ec9-bd5b-8459
    ba8de0db/activity?limit=100000&sort=createdAt&order=DESC&state=480&
    currency=USD&country=US"
extract_data(shoe_name, url, feature)
```

B Additional Data Visualization

Figure 9: Nike SB Dunk High Supreme Navy Median Ask, Bid, and Sale Prices by Size

Figure 10: Nike SB Dunk High Supreme Navy SD Ask, Bid, and Sale Prices by Size

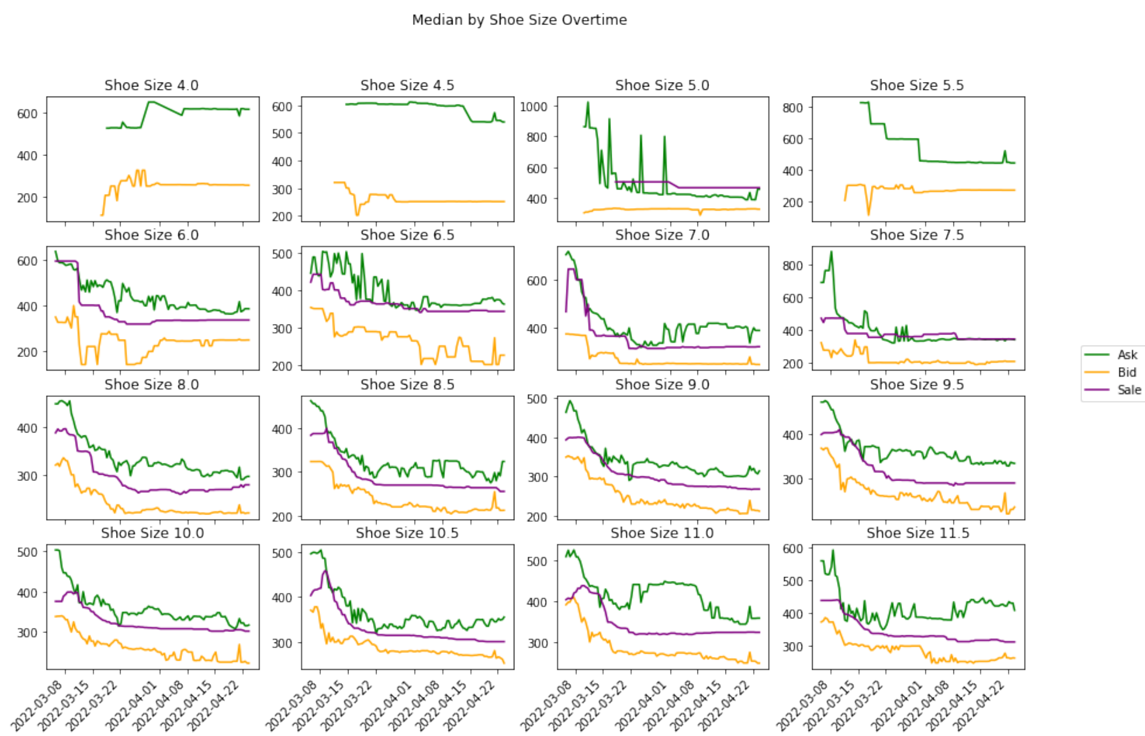


Figure 11: Nike SB Dunk High Supreme Brazil Median Ask, Bid, and Sale Prices by Size

Figure 12: Nike SB Dunk High Supreme Brazil SD Ask, Bid, and Sale Prices by Size

Figure 13: Nike SB Dunk High Supreme Black Median Ask, Bid, and Sale Prices by Size

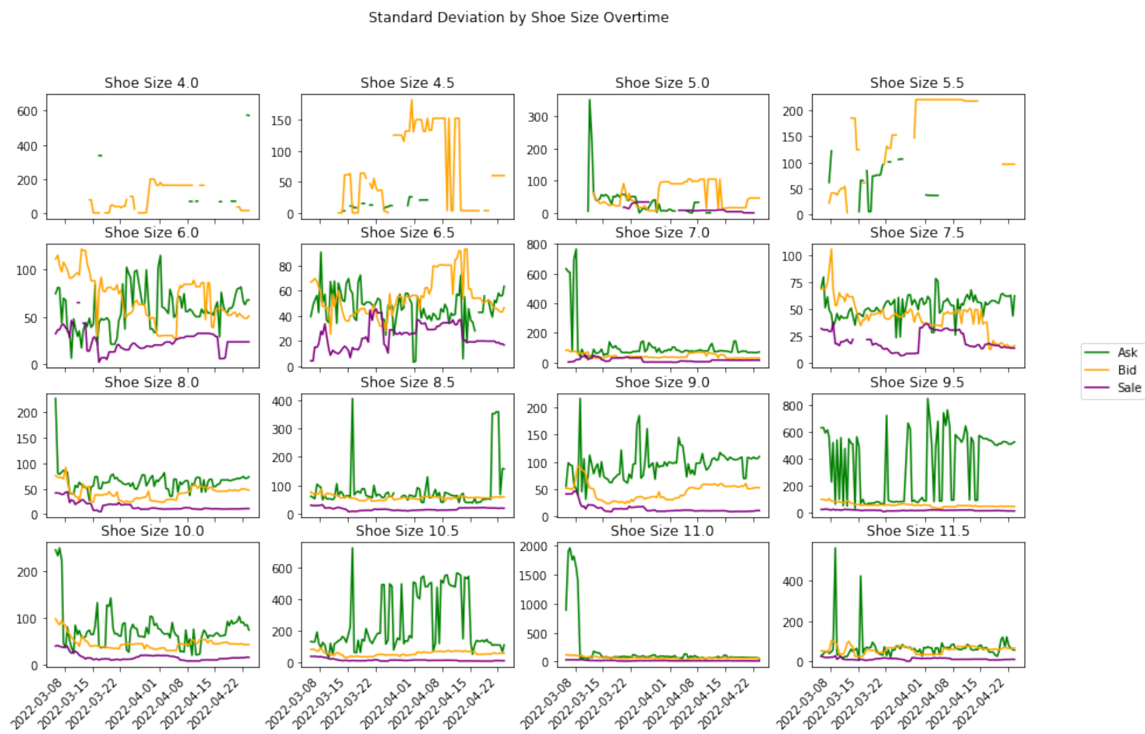


Figure 14: Nike SB Dunk High Supreme Black SD Ask, Bid, and Sale Prices by Size

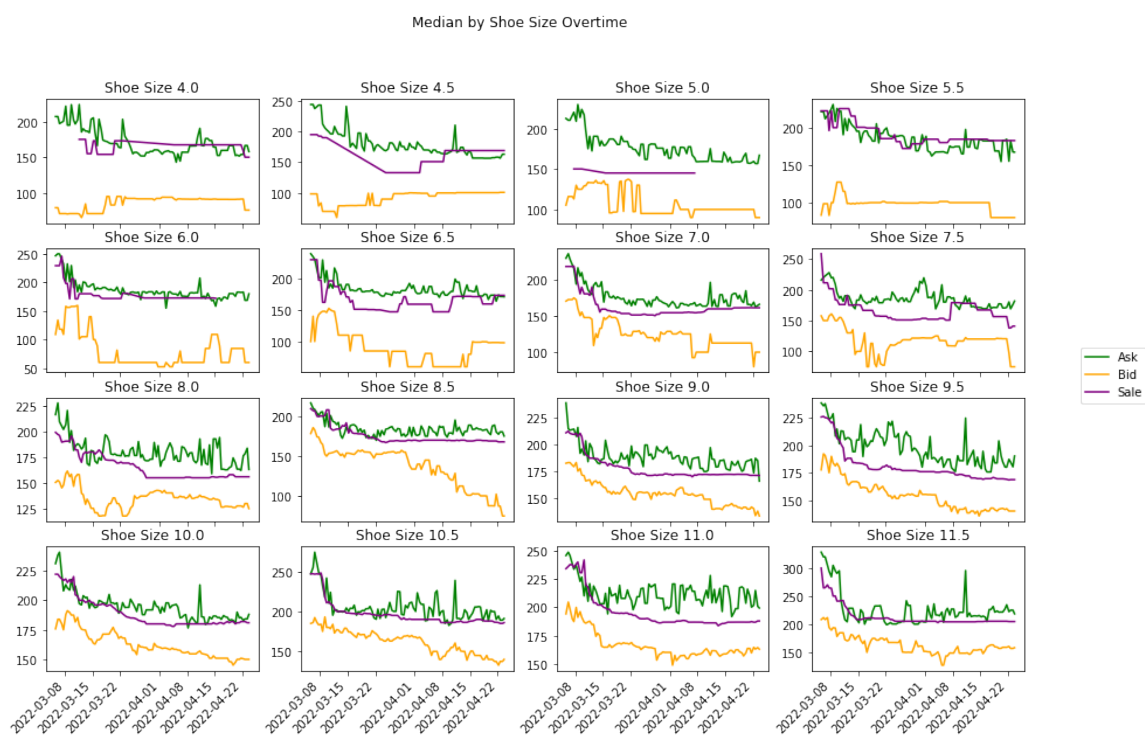


Figure 15: Nike SB Dunk High Pass Median Ask, Bid, and Sale Prices by Size

Figure 16: Nike SB Dunk High Pass SD Ask, Bid, and Sale Prices by Size

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