ETH
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Lecture with Computer Exercises:
Modelling and Simulating Social Systems with MATLAB

Project Report

Shoe Resale Market Model from Fashion Trends

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Contents

1 Abstract

A unique secondary market has boomed in the past five years: sneakers and other fashionable apparel are being sold outside retail stores for 150-1000 % the retail market price. Demand is high for these items of limited quantity which offer social status and a feeling of uniqueness to their owners. This project simulates this market to understand how its dynamics differ from a traditional stock market. A financial model was created in MATLAB to simulate buyers and sellers of shoes with variable prices and social desirability.

2 Individual contributions

Both team members equally developed the research questions, goals of the project, the final report, and presentation. They also worked together to resolve issues in their individual tasks.

3 Introduction and Motivations

Shoes have acquired a cultural significance in parts of the modern world. Many shoes manufacturers partner with trend setters to create stylish limited quantity shoe models. In recent years, these shoes have been selling out quickly in the retail market and then resold in a secondary market with markups reaching over 1000 % [1]. The sum of these transactions is estimated to be over 1 billion US dollars this year [2].There are many different players in this secondary market. This project seeks to model transactions in the secondary market and identify the best strategy for each type of player.

3.1 Motivation

There is a great pool of research on simulating traditional stock markets [3, 4]. We want to see how applicable these techniques are to a market which is relatively new and has not been studied academically. The resale market for sneakers is also features more diverse players than the stock market. Maximizing financial returns is not the only motivation for some people in the sneaker resale market. The sneakers themselves offer a social value from their rarity and style that many people want to own [1]. We believe it is this desire which creates very large fluctuations in market price above initial retail price. The physical condition of a shoe is also important to its value; pristine shoes sell for more than ones that have been worn more.

This market offers some unique challenges for simulation. The social value of a sneaker is dependant on many things, who is promoting them, the brand, the color, the condition, and its rarity. Like old cars, some sneaker models increase in value simply because they are vintage and viewed as "classics" that defined a brand. These factors are not equally valued in the eyes of the different traders in the market. The

traders themselves have different incentives: some want to maximize the stylishness of their sneakers, some want to collect the most interesting sneakers (sometimes not even wearing them), and some are simply seeking to profit as middlemen serving the other groups. Some consumer exhibit behavior that is a combination of the previous factors. The various types of traders create a more complicated and perhaps more interesting trading dynamic than the one seen in the stock market.

3.2 Fundamental Questions

- How does the proportion of sneakers to agents affect price?
- How is price affected by the number of competing sneaker brands?
- Which market parameters are the most impactful on price?
- What behaviors of the sneaker market differ from a standard stock market model?

The first question is important to sneaker manufacturers. They decide the number of sneakers they will make and the initial selling price. The manufacturers want to maximize profit. But they receive an intangible benefit to their brand's reputation and desirability due to excitement and promotion in the resale market [1]. Thus some firms may not sell a shoe for the highest price they could in the present, because they want to create excitement and demand for their brand in the future. Knowing how many sneakers are needed to satisfy a given number of agents would help manufacturers optimize their business.

The second question is important to manufacturers and profiteers. The market has many competitors with limited product differentiation. It is important to understand how competitors may induce price competition.

The third question is important to evaluating price sensitivity. By understanding the most important parameters, the people that are represented by our agents may be able to take information about the real values of those parameters and better inform their own strategies for trading in the market.

The fourth question is important to the academic scope of this work. If there are few differences, it indicates that existing modeling techniques can be applied to a broader array of problem types. If there are significant differences, this opens up new avenues of research to more deeply understand the behavior of non-traditional markets. Appropriately modeling and understanding those different behaviors may offer greater insight into the subtle dynamics of economic systems.

3.3 Expected Results

We expect to find that reducing the ratio of sneakers to agents will increase resale price and create more volatility in the market. Lower supply for given demand should create higher prices in accordance to basic economic theory. If there are too few shoes in the market, the agents may not be able to afford them, which would reduce transaction frequency. This would correspond to a loss of excitement over a specific shoe type.

If the sneaker to agent ratio is constant, but there are more competing brands, the prices should also go down. The model gives preference to owning a greater variety of sneaker types for the collectors and socialites. This should result in prices going down as agents are able to bid on a wider variety of products.

We expect the sneaker to agent ratio to have a larger impact on price than the number of competing brands. This parameter affects the available supply. From an economic perspective the available supply should affect price more than the presence of competition.

There should be some noticeable differences between stock market models and our sneaker market model because our trader agents have behaviors not seen in the stock market. We expect that the different agents see different rates of return based on their preferences for social status or economic value.

4 Description of the Model

This is a complex market with many dynamics, players, and price factors - many of which are not perfectly rational. So we identified the core elements of the model that lent themselves to computational simulation. We built on previous research by Raberto *et al.* [3] which uses an agent based model to simulate a stock market.

In Raberto *et al.*'s model [3], the agents are traders who buy and sell stocks. The sneaker market behaves in a similar way with buyers and sellers. The difference is that non-price value of sneakers is modelled as an additional parameter. Thus, the shoes that are bought and sold are represented by two numbers: a price and a "social status". The social status parameter represents the non-price based appeal of the shoe. The social status quantifies how people in the real world would view the stylishness, quality, and condition of a shoe. The agents respond to the social status in different ways and have different end objectives. The four agents we model are the trendsetters, socialites, collectors, and profiteers.

4.1 Description of Agents

The trendsetters are agents that bring shoes into the marketplace. They represent different shoe brands and create the initial social status. As trendsetters they do not need to buy shoes.

The socialites are agents who buy and sell sneakers to optimize social status. These correspond to people in the real world that buy trending sneakers, wear them for a short time, and sell or exchange them for different sneakers.

The collectors are agents who buy but do not sell any sneakers. They correspond to people in the real world that want to buy the best shoes which will retain value. They take shoes out of the marketplace

and often display them in personal collections or shoe racks. In the real world, these collectors may also sell some of their shoes, or buy multiple pairs so they can wear some while keeping another pair in pristine condition. Collectors in the real world often have one to two hundred different pairs of shoes [1]

Finally the profiteers are agents who buy and sell sneakers to maximize monetary profit. These agents ignore the social status. These correspond to people in the real world who have little interest in sneakers themselves, but want to capitalize on high mark ups over retail price.

There are many other types of agents that could have been modelled, but the complexity of their addition did not justify their lesser importance to the market. For example, individuals in the real world may switch roles based on their own incomes and personal impulses. There are counterfeit shoes in the market, scammers who take people's money without sending anything in return, trading bots, and other miscellaneous occurrences that happen less frequently than the core behaviors we modelled.

When modeling the agents, each of them will have different properties which will differ from one type of agent to another. This fields include the social status of the agent, which varies over time; the desire to buy new shoes, defined depending on the agent; and some initial money to start trading.

These agents are classified into buyers and sellers, depending on their type and several factors. Socialites will become sellers if they do not have more money to buy and they have some items, or if they do not want to wear their sneakers anymore. Profiteers however, become sellers when the average value of their assets is higher than the average selling price of the market, trying to maximize their profit. Whenever these two agents sell all their items, they become buyers again.

4.2 Trading Environment

The environment for the agents is a closed market, where the items are released by the trendsetters and then interchanged between the different agents according to their needs and desires. The agents are fixed, meaning they don't change from one type to another and there is no exit or entry of agents into the market. The shoes being traded may depreciate in value to a point where they are no longer sold in the market. But new shoes will be periodically released into the market to ensure demand is met. It is also assumed the agents have supplemental sources of income which is paid out regularly in set periods (representing their real world salary from a job). This ensures that new items in the market are affordable by some people.

The market operates at every time step, which corresponds to a day of trading. Buyers and sellers will decide their individual prices for a day of trading. Buyers that are unable to buy shoes during a trading day will generally increase the price they are willing to pay on the next day. Sellers that are unable to sell a shoe at a price will generally decrease the price they are willing to pay. The time it would take to ship sneakers from buyers to sellers is ignored.

The transactions only occur when certain conditions are met. These conditions depend on the buying price of each buyer and the selling price of each item. The former has to be higher than the latter for the transaction to take place. Additionally, the social status of the item is tied to a random variable. Sneakers with less social status are less likely to be sold in the market.

5 Implementation

5.1 Inputs

The inputs required by the user to run this simulation are mainly associated with the size of the simulation. The number of agents to be simulated and the amount of sneakers introduced in the market have to be set. In order to simulate the behaviour of this market, the model should be run with a larger number of agents than items sold. If this is not true the economic system breaks down because the items are no longer limited, everyone could buy one. This is true for the real world: there are many more people interested in buying the limited edition shoes than the available supply of those shoes. The scarcity creates value in all economic systems.

Furthermore, an initial price for the buyers needs to be set. This sets an initial condition and only affects the buying prices in the beginning of the simulation. The buying and selling prices are modified later depending on offers and demand.

The last inputs required are the amount of brands for the sneakers and the duration of the simulation, which is given by the days the user wants to simulate. The former input has to be reasonable according to the amount of agents introduced in the system and the amount of items.

With these inputs set, the model is set to run and simulate the evolution of the model explained in the previous section.

5.2 Outputs

The outputs produced by the program are a set of graphs showing the evolution of different parameters through time as well as some final characteristics that define the agents and their behaviour. These graphs and figures will be discussed in the following section 6.

5.3 Fixed Simulation Parameters

For the simulation to run more parameters than the ones provided in the input routine are needed. These values are set in the code, and they can either have a fixed value during the whole simulation or vary randomly as time goes on. The frequency with which brands release new sneakers to the market is set to be one of those random values calculated in the code, as well as the change in social status of the items through time. The fixed values include for example how much the buying and selling prices are increased or decreased depending on whether the agent performed a transaction or not. These values are weighted with the desire of the buyers to buy the items.

These parameters have been optimized in the code through many iterations so that the model represents the real behaviour of the market and doesn't produce results far from examples we found in our research. This optimization allowed us to better understand the important market dynamics and critically think about why values had to be in certain ranges.

5.4 Code Structure

In the code's first steps, the data structures are created and initialized. There are two main data structures, buyers and sellers, which are then selected to be one of the agents described previously. Initially only trendsetters are sellers, as they are the ones to introduce the sneakers into the market. Then the rest of the agents become potential buyers.

Each buyer is then assigned a set of attributes corresponding to their initial money, social status, and desire to buy items. Sellers on the other hand are assigned assets which are assigned randomly to one brand. A check is made to ensure each brand is represented by a trendsetter. Each brand is then assigned a random social status and initial price, which transfers to the trendsetters belonging to that

brand. This way the items get their initial selling prices and social value.

Before running the simulation, some parameters are initialized, such as the increase or decrease in prices depending on the transaction. The code starts the simulation, which performs the purchase of the item, the change in the agents' attributes according to their actions and the update of the items social status as time progresses.

The first lines of the loop for the simulation calculate all the desired information in each iteration, such as the average selling price or the average buying price of each different type of agent. Then the trading operation between the agents occurs. Transactions happen only when the conditions mentioned in subsection 4.2 are fulfilled. With the purpose of approximating reality, the constraint that one buyer can only buy one item per day has been applied into this model.

The next lines in the code (shown in A) vary the different parameters associated with each agent. For buyers, the buying prices are adjusted, the social status is calculated based on the items they own, and the desire changes depending on their agent type. Sellers lower their selling prices if they did not manage to sell one item.

Following these changes, the agents are moved from buyers to sellers and the other way around according to the factors explained before. Both sellers and buyers retain their values for desire, social status, buying price, etc, as they are the same people that move from one side to the other of the market.

Finally, the status of the items is changed in each iteration. Due to depreciation, items lose a random amount of their social status, making it less likely to be bought. This also accounts for the loss of value because of wear. Each brand is also assigned a factor equating to 'vintageness', so some shoe brands increase in social status. However, depreciation tends to be bigger in our time scales and the social status of the shoe decays in time.

Once all of this actions are performed, the new day begins with the transactions between the new buyers and sellers according to their new parameters.

6 Simulation Results and Discussion

To answer the fundamental questions proposed in subsection 3.2, several simulations have been carried out. The different simulations varied the input parameters to test the most influential parameters.

6.1 Nominal Test

We perform a baseline simulation which is used as a comparison for our results. The parameters of the baseline are conservative values that ensure the model is stable. The results from this simulation are our reference for further runs and changes to the input parameters.

The number of agents chosen for this simulation is $N = 1000$ with $n_{items} = 800$ which will be divided into 4 different brands, which will be initialized randomly. The starting price for the buyers in this market is $p = 700$ currency units. This market will be modelled for one year, so the time steps for the iteration will be $t = 350$ days.

The following graphs illustrate the results obtained with this simulation. In *Figure* 1 the average of the buying prices from all the different agents and the global average of the selling price. It can be seen the different strategies followed by each type of agent. The buying prices from the socialites and profiteers do not present much difference from one another. They interchange the roles of sellers and buyers once all the items have been released to the market by the trendsetters. As it can be seen, the socialites are the more active in the market, with a buying price closer to the average selling price.

Meanwhile, the collectors follow a very different trend. These agents buy during the first day of the new items, as this items are the ones worth to collect. This makes them run out of money, and therefore their buying prices decay and start rising, as they earn money through time. When new items are introduced, they use this money in order

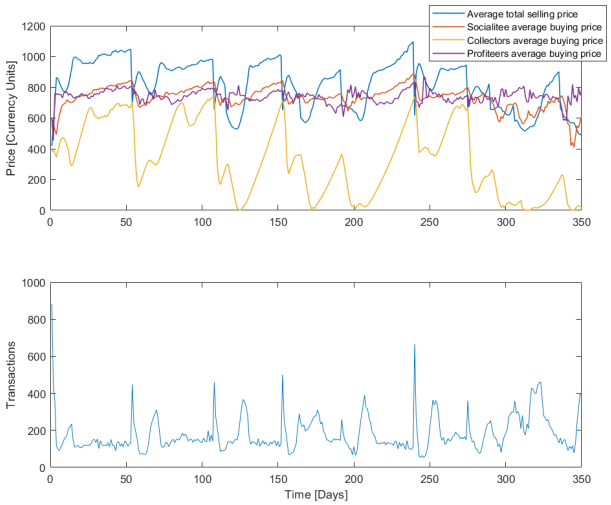


Figure 1: **Top** - Average buying prices from the different buyers and global average price. **Bottom** - Number of transactions each day. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$ and *t=350 days*

to acquire the brand new released sneakers

Furthermore, the average selling price is higher than the average buying price. This corresponds to the real world, where no seller wants to sell for less of what the paid to buy the item. The only points in which the selling price is lower than the buying price is at very selected days, which correspond with the moments when new items are released. This new items have much lower prices than the value of the sneakers already in the market. It is interesting to note how profiteers increase their buying prices during these periods in order to buy more and therefore sell it for a higher price.

Figure 1 also shows the number of transactions in each day. The peaks shown in this graph correspond to the moments when new items are released and when they are starting to get sold in the market as socialites get tired of them and go looking for different sneakers. As time progresses, more items are in the market and the number of

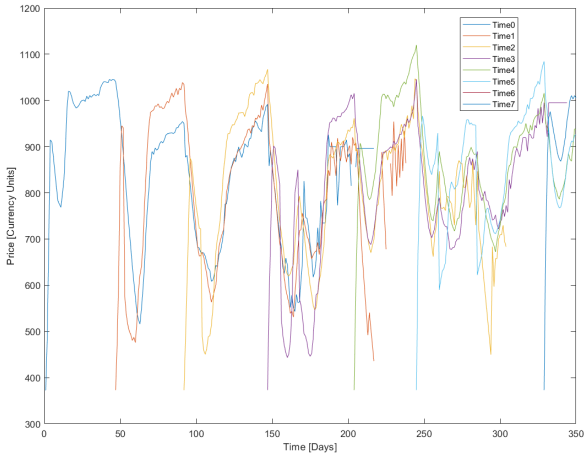


Figure 2: Average selling price of the items introduced in each time period. Time0 being the oldest items in the market and Time7 the newest. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$, *p=700* and *t=350 days*

transactions starts oscillating at the end of the simulation run. This because there are more items to be interchanged and the agents are more active, trading more goods.

The introduction of new items to the market can be observed in *Figure* 2. This graph also shows how newer items have a higher selling price, as they are more demanded. The last two graphs show also how the selling price of the items introduced in one period increases during that period until new sneakers are introduced. This is because items start coming out of the market as they have a social status below a certain threshold, or they are property of the collectors, being also out of the market.

Another interesting result to look at how the different brands evolve through time. This brands are affected by the depreciation and by a random 'vintageness' factor, which is equal for each brand but it is created randomly every iteration. The result of this behavior can be seen in *Figure* 3. This graph shows how competitive this market is,

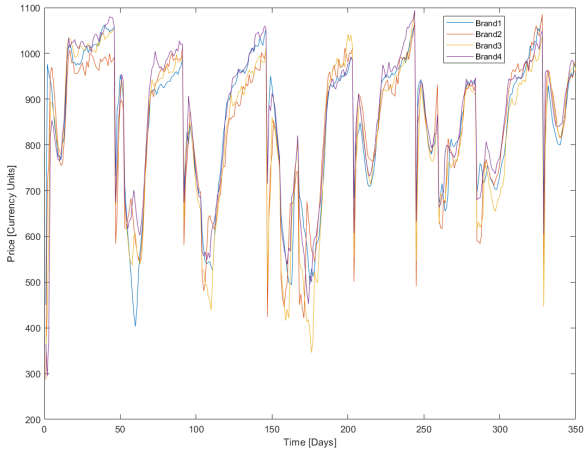


Figure 3: Average selling price per brand. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$, *p=700* and *t=350 days*

where the four different brands have a similar buying price. However, the best-selling brand changes from time period to time period. This reflects the reality, as different designs and models from the same brand have a bigger or smaller impact on society. When looking through a sort period of time, it can be seen how 'vintageness' affects randomly to the brands, as their selling prices oscillates within days.

The results of these transactions in the market can be seen in *Figure* 4, where the net profit of the profiteers can be seen. This profit is calculated as the difference of what they paid for the items and what they sold it for. When the market closes, the value of each profiteer's inventory is added, as this is money they have invested. However, this leads to some error, as for profiteers who are still buyers, they are selling it for a lower price and therefore losing money, which would not be the behavior of the modelled profiteer.

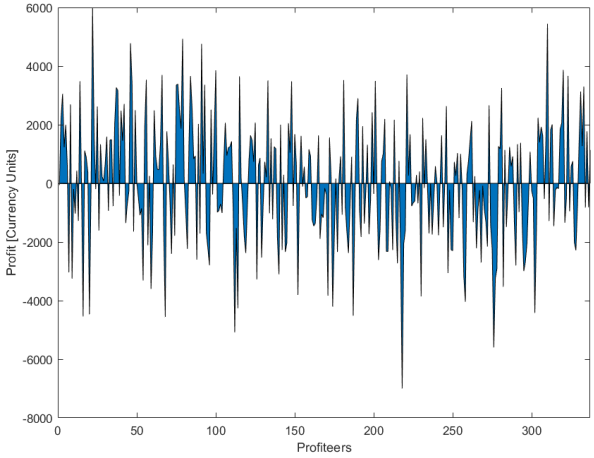
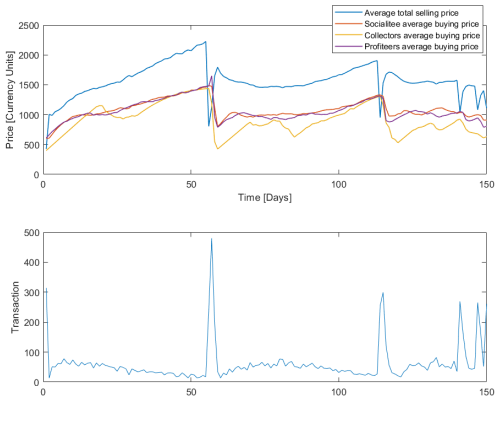


Figure 4: Profit made by each profiteer at the end of the simulation. Current inventory is added. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$, *p=700* and *t=350 days*

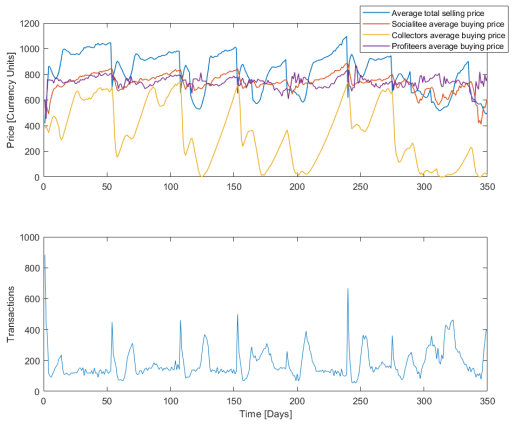
These results from the nominal inputs can be now used to analyze how the outputs of the market vary when changing the inputs and therefore answer the fundamental questions.

6.2 Effect of Ratio of Sneakers to Agents

To answer the first question, the following simulation was done. The number of agents was kept constant, *N=1000*, the number of brands $n_{brands} = 4$ and the initial price *p=700* were the same and the brands were initialized randomly, but the number of items was reduced from 800 to $n_{items} = 200$. This way, there are not enough items to satisfy all the agents and the competition between them increases. Additionally, the simulation lasted only *t=150* days, as the difference can already be seen in this short period of time and the evolution of the market in time would follow the same trends as in the beginning of it. Similar simulations were performed where the 10:2 ratio of agents to items was retained, but their magnitude varied, using *N=8000* and $n_{items} = 1600$



(a) **Top** - Average buying prices from the different buyers and global average price. **Bottom** - Number of transactions each day. Simulation ran with *N=1000*, $n_{items} = 200$, $n_{brands} = 4$, *p=700* and *t=150 days*



(b) **Top** - Average buying prices from the different buyers and global average price. **Bottom** - Number of transactions each day. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$ and *t=350 days*

Figure 5: Comparison between the different values of prices and number of transactions for the nominal case and the low amount of items case

for a larger number of agents and using *N=100* and $n_{items} = 20$ to simulate fewer agents. The overall behavior was the same in these cases, differing only as expected due to the random parameters.

The first results of this simulation can be seen in *Figure* 5. These graph shows the comparison between the nominal and this case of the evolution of the average of the buying and selling prices. Comparing these graph with *Figure* 1, it can clearly be observed that the prices are much higher when the number of items decreases. As said in the expected results, this is what should happen in an environment where supply is strictly limited and the demand is high. The number of transactions is also displayed. This value is significantly lower, as the number of items available is lower and their prices are much higher, meaning not everyone can afford it.

This difference is more clearly seen in *Figure* 6. The average trans-

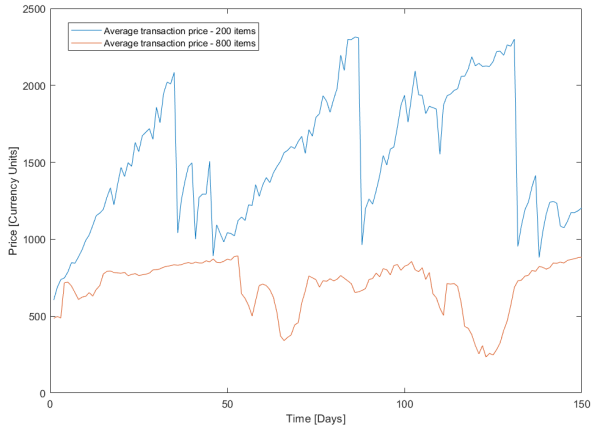


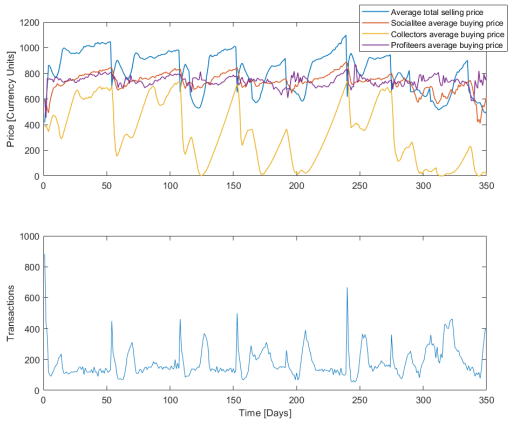
Figure 6: Comparison of average transaction prices per day for both cases: $n_{items} = 800$ and $n_{items} = 200$. Simulation ran with *N=1000*, $n_{items} = 200$, $n_{brands} = 4$, *p=700* and *t=150 days*

action prices of each day are represented in this graph for both cases, nominal and low amount of items.

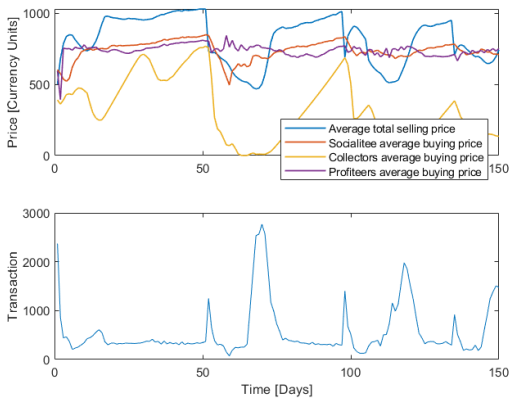
6.3 Effect of Number of Brands on the Price

This simulations investigates how the agents behave when there are many brands to choose from with different attributes. In this case $n_{brands} = 10$ and all other parameters are the same as the nominal case. This implies that the simulation cannot be with 100 agents any longer, as this would lead to too few trendsetters and some brands would end up with no representation in the market and would not release their items. Therefore, the number of agents is set to be *N=2500*. As the number of agents increases, so has to do the number of items, or the model would have the same behavior as in the last study. Thus, the number of items in this study is $n_{items} = 2000$. The rest of parameters are the same as the study in subsection 6.2.

The following figures show the behavior of the market under these



(a) **Top** - Average buying prices from the different buyers and global average price. **Bottom** - Number of transactions each day. Simulation ran with *N=1000*, $n_{items} = 200$, $n_{brands} = 4$, *p=700* and *t=150 days*

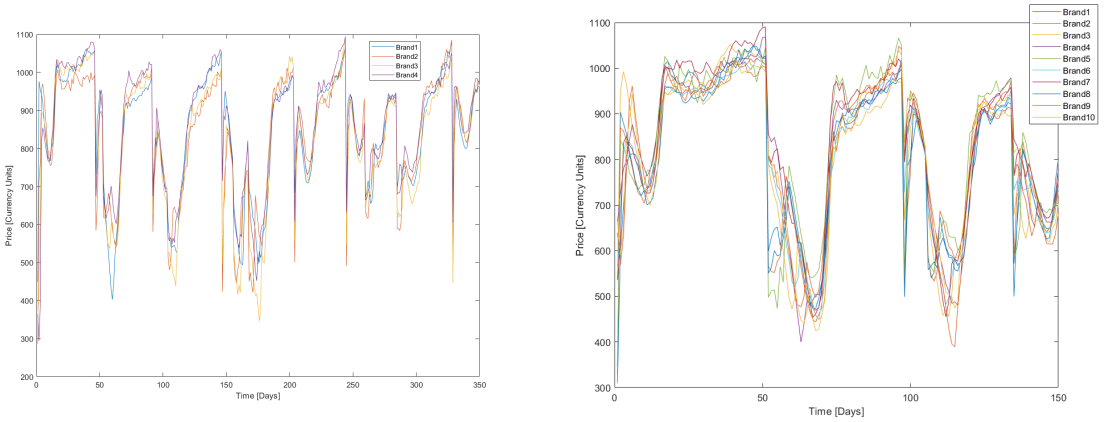


(b) **Top** - Average buying prices from the different buyers and global average price. **Bottom** - Number of transactions each day. Simulation ran with *N=2500*, $n_{items} = 2000$, $n_{brands} = 10$ and *t=150 days*

Figure 7: Comparison between the different values of prices and number of transactions for the nominal case and the high number of brands case

conditions. *Figure* 7 illustrates the comparison between the nominal case and the case discussed in this section. The prices seen in *Figure* 8b are very similar to the ones obtained for the nominal case. This is implies that the amount of brands does not have a big impact on the price, a result that was expected as the ratio of items and agents has been kept constant. Competition between brands is not a big factor to take into account for the agents.

However, and as shown in *Figure* 8, there is a bigger variance between the prices for each brand. This is also expected, as more brands would lead to more options when buying and the depreciation factor and 'vintageness' feature affects differently each brand and shoe. More difference would be seen if there was a bigger difference between brands, but this would involve modelling several parameters of the brands, which is not the objective of this work and it would increase



(a) Average selling price per brand. Simulation ran with *N=1000*, $n_{items} = 800$, $n_{brands} = 4$, *p=700* and *t=350 days*

(b) Average selling price per brand. Simulation ran with *N=2500*, $n_{items} = 2000$, $n_{brands} = 10$, *p=700* and *t=150 days*

Figure 8: Comparison between the selling prices for each brand for the nominal case and the high number of brands case

greatly the complexity of the model.

6.4 Most Influential Parameters

Once these factors have been analyzed, it is clear to see that the amount of items released in the market is a great way to modify the behavior of it. This is of great value to the sneakers brands, which can adapt the amount of items released in order to increase the selling price but without selling any item. Having a surplus of items in the market would also lead to a different behavior than the one presented in this approach, but it would not have a negative impact on the consumers, as the market would be saturated with items and there would be no competition between the agents in order to achieve their desires.

The initial price of the buyers would have a minor effect in the beginning of the simulation, as it would change the initial amount of assets bought if it was below the selling price, which would not

represent the reality, since socialites, profiteers and collectors want to buy first hand items for their own goals. Nevertheless, the influence would decrease as time goes by, reaching the same results explained in this report.

Another important parameters that have an effect in the market are more intrinsic parameters such as the price variation of the items depending if they are being sold or bought, depreciation and 'vintageness', inflation if the simulation time was over years, etc. However, modifying these parameters would change the behavior of the model, making it less approximate to reality. Therefore, even though these values affect largely the model, they are not values that should be changed from one simulation to another.

6.5 Difference between Stock Market and Retail Shoe Market

The big difference between these two markets is the effect of personal value of the items and their intangible value. This value is what is accounted for in the social status term in this model presented, where the value of the shoe not only depends on the time it has been in the market, but who owns it and who released and made that sneaker. Therefore, the shoe retail market has much more factors that could influence a potential buyer or seller.

This is what makes it much more difficult to model and simulate, as it needs to take into account parameters that cannot be expressed by any number or analytic expression. The approximation made in this model is quite simple but reflects the core of this human aspect of the market, giving a vague idea of how this influences the prices and transactions.

7 Summary and Outlook

The initial results of our simulation show interesting behavior worthy of further study. There are many potential refinements to the code that could increase its accuracy and computational efficiency. Further research should also be done to incorporate real world data into the simulation. There is a wealth of useful data about consumers in the market on various social media platforms.

7.1 Limitations and Simplifications

Many simplifications had to be made to create this model of the sneaker resale market. The attributes of a variety of different products and people had to be simplified. Fashion is a very subjective topic, which makes objective modeling difficult. Several arbitrary parameters must be made to attempt to model human preferences.

Due to processing power, we only simulated up to 8000 agents. There are vastly more people active in this market, on the order of millions. And these people do not trade in the market everyday. Only a few are active daily, others seasonally, and others only on special occasions when they have a surplus of disposable income.

As previously mentioned, counterfeit goods and scammers are active in this market but were not simulated. They drain peoples' available funds. The need to be cautious in the marketplace creates barriers to rapid transactions.

The code itself could be significantly optimized. It was written in small iterations, so many parameters were added as their behavior was understood. This caused our data structures to be fragmented in computer memory which increase computation time.

Further development of this simulation should experiment to find data structuring that is optimal for holding many parameters than can

be exchanged between agents that have different attributes. API tools could also be used to access social media and shoe trading websites to qualify actual market activity. This could improve the ability to identify relevant market parameters and tune existing ones to behave like the real market.

7.2 Conclusion

To conclude, this report shows how a shoe retail market, or in essence, any retail market could be modelled through an agent-based model, taking into account, not only mere financial and analytic attributes, but also the human dimension of the market, which in the end is what makes this limited edition shoes such a valuable thing.

It is also shown how this market behaves under nominal conditions that try to approximate the real world, and what would happen if some of the parameters of the model would change, and how can the different agents profit and use these changes for their own benefit.

8 References

[1] L. Chow. You See Sneakers, These Guys See Hundreds Of Millions In Resale Profit, October 2014. URL https://fivethirtyeight.com/features/you-see-sneakers-these-guys-see-hundreds-of-millions-in-resale-prof

[2] L. Steinberg. The Profitable Hidden Sneaker Market, September 2018. URL https://www.forbes.com/sites/leighsteinberg/2018/09/17/the-profitable-hidden-sneaker-market/#319df41c5925.

[3] M. Raberto, S. Cincotti, S. M. Focardi, and M. Marchesi. Agent-based simulation of a financial market. *Physica A Statistical Mechanics and its Applications*, October 2001.

[4] P. Bak, M. Paczuski, and M. Shubik. Price Variations in a Stock Market with Many Agents . *Physica A Statistical Mechanics and its Applications*, December 1997.

A Appendix A

```
function [] = Financial_Model(n_agents, n_items, price, nbrands, rndbrand, timesteps)
%% This Function uses its inputs to run a simulation of a secondary market for sneakers.
%The inputs are:
% n_agents : the total number of agents in the model
% n_items : the total number of shoes in the model
% price : the starting price of a shoe  (maybe shouldnt be fixed here?)
% nbrands : the number of competing shoe brands
% rndbrand : a parameter (0 or 1, to randomize the appeal of the shoes)
% timesteps : the length of time simulated, one time step is one day

% %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%   CAUTION: THE NUMBER OF BRANDS MUST BE LOWER THAN NUMBER OF           %
%   TRENDSETTERS. THERE MUST BE MORE AGENTS THAT ITEMS TO MAKE A         %
%   SENSIBLE ECONOMICA MODEL. OTHERWISE THERE IS NO SCARCITY             %
% %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```
17 %The outputs are a series of graphs depicting
       price, profit, and social
18 %status of the agents under various conditions
19
20
21 %% Data Structure CREATION
22
23 close all
24 agent = struct('money', 0, 'soc_stat', 0, 'items'
       , 0, 'desire', 0, 'mode', 0, 'buysell', 0, '
       sprice', 0, 'bprice', 0, 'bought', 0, 'sold', 0,
        'keep', 0);
25 seller = struct('money', 0, 'nitems', 0, 'socstat
       ', 0, 'bprice', 0, 'sold', 0, 'mode', 0, '
       initmoney', 0, 'brand', 0, 'gain', 0);
26 buyer = struct('money', 0, 'nitems', 0, 'socstat'
       , 0, 'desire', 0, 'bprice', 0, 'bought', 0, '
       mode', 0, 'initmoney', 0, 'keep', 0, 'bdes', 0,
       'gain', 0, 'avgiprice', 0);
27 brnd = struct('price', 0, 'socstat', 0);
28
29 % The brand variable takes into account from which
        brand is the setter
30 % selling the shoes. 0 - would be for independent
       sellers (The socialitees
31 % and profiteers that are selling something)
32
33 % The 'keep' variable is only used by the
       collector to know if they will sell
34 % their stuff in order to get the new released
       items
```

```
35
36 %The field initmoney is just only by the
       profiteers to know when they have
37 %achieved their goal of maximizing their money
38
39 %Mode indicates if the agent is a setter,
       socialitee, collector or
40 %profiteer. 1 - set, 2 - soc, 3 - col, 4 - prof
41
42 %Buysell indicates if the agent is a seller or a
       buyer. 0 - Seller 1 -
43 %Buyer
44
45 % The desire parameters measures how much the
       agent wants to buy the item.
46 % For socialitees this value will be higher, and
       for profiteers &
47 % collectors it will be smaller, but the
       collectors' value will rise as
48 % time goes on because items will be more
       appreciated. For trendsetters
49 % this value will be 0, since they do not want to
       buy their own stuff
50
51 %% Assigning Roles to each agent
52 people = repmat(agent, n_agents, 1);
53 brand = repmat(brnd, nbrands, 1);
54
55 n_soc = 0; n_prof = 0; n_coll = 0; n_set = 0; %
       variable initializations
56
```

```
57 while(n_soc<=0 || n_prof<=0 || n_coll<=0 || n_set
     <=nbrands*3)
58 n_coll = randi([round(n_agents*0.075), round(
     n_agents*0.1)]);
59 n_soc = randi([round(n_agents*0.4), round(n_agents
     *0.6)]);
60 n_prof = randi([round(n_agents*0.3), round(
     n_agents*0.6)]);
61 n_set = n_agents - n_prof - n_soc - n_coll;
62 end
63
64
65
66 % Assign the sellers to each brand
67 if rndbrand == 0 %The prices and social status of
     the brand are not randomly set, they are hard
     coded
68     nbrands = 4;
69 end
70
71 sperbrand = zeros(1, nbrands);
72 while (sperbrand) < 3 % There should be more than
     3 trendsetters for each brand
73     for i=1:nbrands
74         sperbrand(i) = round(n_set/nbrands);
75         exsel = mod(n_set, nbrands);
76     end
77     for i=1:exsel
78         index = mod(i, nbrands);
79         sperbrand(index) = sperbrand(index) + 1;
80     end
```

```
81      for i=1:nbrands-1
82          el = round((rand*2-1)*round(n_set/(3*
              nbrands)));
83          sperbrand(i) = sperbrand(i) - el;
84          sperbrand(i+1) = sperbrand(i+1) + el;
85      end
86      tset = sum(sperbrand);
87      if tset > n_set
88          for i=1:tset-n_set
89              index = mod(i, nbrands)+1;
90              sperbrand(index) = sperbrand(index) - 1;
91          end
92      end
93      if tset < n_set
94          for i=1:n_set-tset
95              index = mod(i, nbrands)+1;
96              sperbrand(index) = sperbrand(index) + 1;
97          end
98      end
99  end
100 % keyboard;
101
102 sellers = repmat(seller, n_set, 1);
103 buyers = repmat(buyer, (n_agents-n_set), 1);
104
105 %% Initialize the number of items each agent has
      and the money they have
106 el_items = 0;
107 nitems = n_items;
108
109 for i=1:n_set % Assign values to the trendsetters
```

```
110     people(i).money = (randi([2, 10])/10)*10e6;
111     people(i).nitems = round(n_items/n_set) - 1;
112     el_items = el_items + people(i).items;
113     people(i).soc_stat = randi([80, 100]);
114     people(i).desire = 0; % Trendsetters have no
          desire to buy their own goods
115     people(i).mode = 1;
116     people(i).buysell = 0;
117 end
118
119 n_items = n_items - el_items;
120 while n_items > 0
121     p = randi([1 n_set]);
122     people(p).nitems = people(p).nitems + 1;
123     n_items = n_items - 1;
124 end
125
126 for i=n_set+1:n_set+n_soc % Assign values to the
    socialitees
127     people(i).money = (randi([15, 25]))*1e2;
128     people(i).nitems = 0;
129     people(i).soc_stat = randi([5, 20]);
130     people(i).desire = rand()*30+70;
131     people(i).mode = 2;
132     people(i).buysell = 1;
133 end
134
135 for i=n_set+n_soc+1:n_set+n_soc+n_coll % Assign
    the values to the collectors
136     people(i).money = (randi([15, 25]))*1e2;
137     people(i).nitems = 0;
```

```
138         people(i).soc_stat = randi([5, 20]);
139         people(i).desire = rand()*10+50;
140         people(i).mode = 3;
141         people(i).buysell = 1;
142         people(i).keep = rand();
143     end
144
145     for i=n_set+n_soc+n_coll+1:n_agents % Assign the
        values to the profiteers
146         people(i).money = (randi([15, 25]))*1e2;
147         people(i).nitems = 0;
148         people(i).soc_stat = randi([5, 20]);
149         people(i).desire = rand()*30+70;
150         people(i).mode = 4;
151         people(i).buysell = 1;
152     end
153
154     % Assign social status to each item
155
156     item_index = 1;
157
158     for i=1:n_agents
159         for j=1:people(i).nitems
160             items_soc(item_index) = randi([8, 10])*
                people(i).soc_stat/10;
161             item_index = item_index + 1;
162         end
163     end
164
165     %% Put items for sale and make the socialitees,
        profiteers and collectors buy and sell.
```

```
166 % Check the number of sellers & buyers and assign
    the selles & buyers (sellers = setters & buyers
    = everyone else in
167 % the beginning)
168 nsell = 0;
169 nbuy = 0;
170 for i=1:n_agents
171     if people(i).buysell == 0
172         nsell = nsell + 1;
173         sellers(nsell).money = people(i).money;
174         sellers(nsell).nitems = people(i).nitems;
175         sellers(nsell).socstat = people(i).soc_stat;
176         sellers(nsell).mode = people(i).mode;
177         sellers(nsell).initmoney = people(i).money;
178     else
179          nbuy = nbuy + 1;
180          buyers(nbuy).money = people(i).money;
181          buyers(nbuy).nitems = people(i).nitems;
182          buyers(nbuy).socstat = people(i).soc_stat;
183          buyers(nbuy).mode = people(i).mode;
184          buyers(nbuy).desire = people(i).desire;
185          buyers(nbuy).keep = people(i).keep;
186          buyers(nbuy).bsoc = people(i).soc_stat;
187          buyers(nbuy).bdes = people(i).desire;
188          buyers(nbuy).initmoney = people(i).money;
189     end
190 end
191 % Set a price and social status for each brand
192      for i=1:nbrands
193          brand(i).price = randi([300 600]);
194          brand(i).socstat = randi([70 100]);
```

```
195         end
196
197
198 % Put the brand to each seller (setter)
199 h = 0;
200 w = 0;
201 for i=1:nbrands
202     h = h + sperbrand(i);
203     for j=1+w:h
204         sellers(j).brand = i;
205     end
206     w = h;
207 end
208
209 sigmaprice = 0.05;
210 ks = 2.5; %constant for the standard deviation for
      the selling and buying limit prices
211 sigma = ks*sigmaprice;
212 for i=1:n_set
213     for j=1:nbrands
214         if sellers(i).brand == j
215             for k=1:sellers(i).nitems
216                 sellers(i).items(k).price = brand(j)
                      .price*brand(j).socstat/80;
217                 sellers(i).items(k).socstat =
                      normrnd(sellers(i).socstat, 0.5);
218                 sellers(i).items(k).sold = 0;
219                 sellers(i).items(k).time = 0; %This
                      controls when was de object
                      introduced.
220                 sellers(i).items(k).brand = sellers(
```

```
                    i).brand;
221                 end
222             end
223         end
224 end
225
226 % The probability of a socialitees buying an item
    depends on the social
227 % status of the trendsetter that owns the item.
    Therefore, we need to make
228 % that the trendsetters with lower social status
    put their items for sale
229 % with a lower price so that they get bought
230
231 %% Parameters to change something, such as the
    increase or decrease of the buying prices and
    selling prices, etc
232 Pc = 0.7; %probability an item is bought or sold (
    If a random number is higher than this value,
    then the item will be bought. If it is lower, it
     won't be bought
233 i = 0; % Checks the amount of iterations
234 lowp = 35; %How much we lower the selling and
    buying prices of the agents who bought or sold
    something
235 highp = 40; %How much we increase the prices in
    case the agent didn't do anything
236 newitem = randi([45 60]); %How frequent we insert
    new items into the model
237 avgt = zeros(timesteps, round(timesteps/newitem)
    +1); %Preallocate the matrix containing the
```

```
    averages of all the items from one time period
ipt = zeros(timesteps, round(timesteps/newitem)+1)
    ; %Preallocate the matrix for the amount of
    items from one time period
vin = rand(nbrands, 1)*2 + 2; %Get the vintageness
     of the items once for the first iterations
moneypagent = zeros(3, 1); %Save the amount of
    money interchanged by each agent. The order is
                               % 1 - trendsetters, 2 -
                                   socialites, 3 -
                               % profiteers

    for j=1:nbuy %Go through all the buyers and
       assign them their buy prices
        buyers(j).bprice = price*normrnd(1.01,
           sigma)*buyers(j).desire/100; %This
           buying price gets affected by the desire
            of each agent to buy the good
    end

%% Iterate

while ~isempty(sellers) && ~isempty(buyers) && i<
    timesteps
    i = i + 1;
       % Introduce new items each 20 timesteps
    if mod(i, newitem) == 0
        for j=1:length(sellers)
            if sellers(j).mode == 1
                sellers(j).nitems = sellers(j).
                   nitems + round(normrnd(nitems/
```

```
                    n_set, 0.1));
257                 for f=1:nbrands
258                     if sellers(j).brand == f
259                         for h=1:sellers(j).nitems
260                             sellers(j).items(h).
                                price = brand(f).
                                price*brand(f).
                                socstat/80;
261                             sellers(j).items(h).
                                socstat = normrnd(
                                sellers(j).socstat,
                                0.1);
262                             sellers(j).items(h).
                                sold = 0;
263                             sellers(j).items(h).
                                brand = sellers(j).
                                brand;
264                             sellers(j).items(h).
                                time = i/newitem;
265                         end
266                     end
267                 end
268             end
269         end
270         newitem = randi([45 60]);
271     end
272
273     for j=1:length(buyers)
274         buyers(j).bprice = max(buyers(j).bprice, 0)
              ;
275     end
```

```
276
277         for j=1:nbuy
278             buyers(j).bprice = min(buyers(j).money,
                    buyers(j).bprice);
279         end
280
281             spriceavg = 0;
282         bpriceavgsoc = 0;
283         bpriceavgcoll = 0;
284         bpriceavgprof = 0;
285
286         % Get the average buying and selling prices
287         a = 0;
288         c = 0;
289         b = 0;
290
291         avgb(i, :) = zeros(1, nbrands);
292         ipb(i, :) = zeros(1, nbrands);
293         u = 0;
294         for j=1:length(sellers)
295             for k=1:sellers(j).nitems
296                 spriceavg = spriceavg +  sellers(j).
                        items(k).price;
297                 u = u + 1;
298                 avgt(i, sellers(j).items(k).time+1) =
                        avgt(i, sellers(j).items(k).time+1) +
                         sellers(j).items(k).price;
299                 ipt(i, sellers(j).items(k).time+1) =
                        ipt(i, sellers(j).items(k).time+1) +
                        1; %Items per time
300                 avgb(i, sellers(j).items(k).brand) =
```

```
                avgb(i, sellers(j).items(k).brand) +
                sellers(j).items(k).price;
301             ipb(i, sellers(j).items(k).brand) = ipb
                (i, sellers(j).items(k).brand) + 1; %
                Items per brand
302         end
303     end
304     spriceavg = spriceavg/u;
305     for j=1:length(buyers)
306         if buyers(j).mode == 2
307             c = c + 1;
308             bpriceavgsoc = bpriceavgsoc + buyers(j
                ).bprice;
309         end
310         if buyers(j).mode == 3
311             a = a + 1;
312             bpriceavgcoll = bpriceavgcoll + buyers(
                j).bprice;
313         end
314         if buyers(j).mode == 4
315             b = b + 1;
316             bpriceavgprof = bpriceavgprof + buyers(
                j).bprice;
317         end
318
319     end
320
321     for j=1:size(avgt, 2)
322         avgt(i, j) = avgt(i, j)./ipt(i, j);
323     end
324     for j=1:size(avgb, 2)
```

```
325             avgb(i, j) = avgb(i, j)./ipb(i, j);
326         end
327         bpriceavgsoc = bpriceavgsoc/c;
328         bpriceavgprof = bpriceavgprof/b;
329         bpriceavgcoll = bpriceavgcoll/a;
330
331         avg(i, 1) = spriceavg;
332         avg(i, 2) = bpriceavgsoc;
333         avg(i, 3) = bpriceavgcoll;
334         avg(i, 4) = bpriceavgprof;
335         iter(i) = i;
336
337         % Compare buying & selling prices and
              determine whether a purchase is
338         % made or not based on a probability
339         avgsoldprice(i) = 0;
340         ntrans(i) = 0;
341         for k=1:nsell % loop over all the sellers and
              see if any buying price is below the
              associated selling price
342             for j=1:nbuy % Loop over the buyers & as
                    soon as someone buys from the seller,
                    stop the iteration
343                 for h=1:sellers(k).nitems
344                     if (buyers(j).bprice>=sellers(k).
                            items(h).price && rand()>Pc &&
                            buyers(j).bought == 0)
345                         if rand()<(sellers(k).items(h).
                                socstat/100)
346                             ntrans(i) = ntrans(i) + 1;
347                             if buyers(j).mode ~= 3 % If
```

```
                the buyer is not a
            collector, everything
            works fine
348             % If there is a
                    purchase, remove the
                    item from the seller
                    &
349             % put it in the buyer.
                    Subtract the money
                    used for buying
350             % from the buyer
                    account & put it in
                    the seller account
351             sellers(k).nitems =
                    sellers(k).nitems -
                    1;
352             buyers(j).nitems =
                    buyers(j).nitems + 1;
353             soldprice = (buyers(j).
                    bprice+sellers(k).
                    items(h).price)/2;
354             buyers(j).money =
                    buyers(j).money -
                    soldprice;
355             sellers(k).money =
                    sellers(k).money +
                    soldprice;
356             buyers(j).items(buyers(
                    j).nitems).socstat =
                    normrnd(sellers(k).
                    items(h).socstat, 1);
```

```
357                 buyers(j).items(buyers(
                        j).nitems).brand =
                        sellers(k).items(h).
                        brand;
358                 buyers(j).items(buyers(
                        j).nitems).time =
                        sellers(k).items(h).
                        time;
359                 if buyers(j).mode ~= 4
360                   buyers(j).items(
                          buyers(j).nitems).
                          price = sellers(k).
                          items(h).price + (
                          rand()+1)*buyers(j)
                          .items(buyers(j).
                          nitems).socstat*4;
361                 end
362                 if buyers(j).mode == 4
363                     buyers(j).items(
                            buyers(j).nitems)
                            .price =
                            soldprice + (rand
                            ()+1)*buyers(j).
                            items(buyers(j).
                            nitems).socstat
                            *2;
364                 end
365                 buyers(j).bought = 1; %
                        Set a flag so that
                        that buyer doesn't
                        buy anymore this
```

```
366                 iteration
                    sellers(k).sold = 1; % Set a flag to know that the seller has sold
367                 sellers(k).items(h) = [];
368
369             avgsoldprice(i) = avgsoldprice(i) + soldprice;
370             if sellers(k).mode == 1
371                 moneypagent(1) = moneypagent(1) + soldprice;
372             end
373             if sellers(k).mode == 2
374                 moneypagent(2) = moneypagent(2) + soldprice;
375             end
376             if sellers(k).mode == 4
377                 moneypagent(3) = moneypagent(3) + soldprice;
378                 sellers(k).gain = sellers(k).gain + soldprice;
379             end
380             if buyers(j).mode == 4
381                 buyers(j).gain = buyers
```

```
                (j).gain - soldprice;
382           end
383           break;
384         end
385         if buyers(j).mode == 3 &&
              sellers(k).items(h).
              socstat >= 40
386               % If there is a
                    purchase, remove
                    the item from the
                     seller &
387           % put it in the buyer.
                Subtract the money
                used for buying
388           % from the buyer
                account & put it in
                the seller account
389           sellers(k).nitems =
                sellers(k).nitems -
                1;
390           buyers(j).nitems =
                buyers(j).nitems + 1;
391           soldprice = (buyers(j).
                bprice+sellers(k).
                items(h).price)/2;
392           buyers(j).money =
                buyers(j).money -
                soldprice;
393           sellers(k).money =
                sellers(k).money +
                soldprice;
```

```
394                 buyers(j).items(buyers(
                        j).nitems).socstat =
                        normrnd(sellers(k).
                        items(h).socstat, 1);
395                 buyers(j).items(buyers(
                        j).nitems).brand =
                        sellers(k).items(h).
                        brand;
396                 buyers(j).items(buyers(
                        j).nitems).time =
                        sellers(k).items(h).
                        time;
397                 if buyers(j).mode ~= 4
398                   buyers(j).items(
                          buyers(j).nitems).
                          price = sellers(k).
                          items(h).price + (
                          rand()+1)*buyers(j)
                          .items(buyers(j).
                          nitems).socstat*5;
                             %this code is
                          whack
399                 end
400                 if buyers(j).mode == 4
401                    buyers(j).items(
                          buyers(j).nitems)
                          .price =
                          soldprice + (rand
                          ()+1)*buyers(j).
                          items(buyers(j).
                          nitems).socstat
```

```
                *3;
402             end
403             buyers(j).bought = 1; % Set a flag so that that buyer doesn't buy anymore this iteration
404             sellers(k).sold = 1; % Set a flag to know that the seller has sold
405             sellers(k).items(h) = [];
406         avgsoldprice(i) = avgsoldprice(i) + soldprice;
407     if sellers(k).mode == 1
408         moneypagent(1) = moneypagent(1) + soldprice;
409     end
410     if sellers(k).mode == 2
411         moneypagent(2) = moneypagent(2) + soldprice;
412     end
413     if sellers(k).mode == 4
414         moneypagent(3) = moneypagent(3) + soldprice;
415         sellers(k).gain =
```

```
                                    sellers(k).gain +
                                    soldprice;
416                             end
417                             if buyers(j).mode == 4
418                                 buyers(j).gain = buyers
                                        (j).gain - soldprice;
419                             end
420                                 break;
421                             end
422                         end
423                         %buyers(j).bought = 1; % This
                                says that the buyer didn't
                                buy the thing because of its
                                socials status and not
                                because of the money
424                     end
425                 end
426             end
427     end
428         avgsoldprice(i) = avgsoldprice(i)/ntrans(i)
                ;
429
430 %% Adjust the price in each agent depending on
    whether they bought or sold or not
431     for j=1:length(sellers)
432         for k=1:sellers(j).nitems
433             if sellers(j).items(k).sold == 0
434                 sellers(j).items(k).price = sellers(
                        j).items(k).price - 70;
435                 if sellers(j).mode == 4
436                     sellers(j).items(k).price = max(
```

```
                    sellers(j).bprice, sellers(j).
                    items(k).price);
437                 % Profiteers won't sell it lower
                      than what they bought it
438                 % for, they don't want to lose
                    money
439             end
440         end
441     end
442 end
443
444 for j=1:length(buyers)
445     buyers(j).socstat = buyers(j).bsoc;
446
447     for k=1:buyers(j).nitems
448         buyers(j).socstat = buyers(j).socstat +
              0.2*buyers(j).items(k).socstat;
449     end
450 end
451 for j=1:length(sellers)
452     if sellers(j).mode ~= 1
453         sellers(j).socstat = sellers(j).bsoc;
454         for k=1:sellers(j).nitems
455             sellers(j).socstat = sellers(j).
                  socstat + 0.2*sellers(j).items(k).
                  socstat;
456         end
457     end
458 end
459
460 %% Updating Desire of agents
```

```
461     % The desire of the socialitees decreases as
            the have more socstat. But
462     % in increases when they have less social
            status. For the profiteers,
463     % the desire goes with the difference between
            their initial money and
464     % their money now
465     for j=1:length(buyers)
466         if buyers(j).mode == 2 %Only if they are
                socialitees
467             buyers(j).desire = buyers(j).bdes + (
                    buyers(j).bsoc - buyers(j).socstat)
                    *0.9;
468         end
469         if buyers(j).mode == 4 %Only the
                profiteers
470             buyers(j).desire = buyers(j).bdes - (
                    buyers(j).money - avgsoldprice(i))
                    *0.01;
471         end
472         if buyers(j).mode == 3 %Collectors
473             buyers(j).desire = buyers(j).bdes + (
                    buyers(j).bsoc - buyers(j).socstat)
                    *0.1;
474         end
475         buyers(j).desire = max(buyers(j).desire,
                0);
476         buyers(j).desire = min(buyers(j).desire,
                100);
477     end
478     for j=1:length(sellers)
```

```
479         if sellers(j).mode == 2 %Only if they are
              socialitees
480             sellers(j).desire = sellers(j).bdes +
                  (sellers(j).bsoc - sellers(j).
                  socstat)*0.9; %Their desire lowers
                  when they have a high social status
                  and viceversa, it increases when
                  they have a lower social status
481             sellers(j).desire = max(sellers(j).
                  desire, 0);
482             sellers(j).desire = min(sellers(j).
                  desire, 100);
483         end
484         if sellers(j).mode == 4 %Only the
              profiteers
485             sellers(j).desire = sellers(j).bdes -
                  (sellers(j).money - sellers(j).
                  initmoney)*0.01; %Same as
                  socialitees but
486             sellers(j).desire = max(sellers(j).
                  desire, 0);
487             sellers(j).desire = min(sellers(j).
                  desire, 100);
488         end
489     end
490
491     for j=1:length(buyers)
492         buyers(j).avgiprice = 0;
493     end
494     for j=1:length(buyers)
495         if buyers(j).mode == 4
```

```
496                 for k=1:length(buyers(j).items)
497                     buyers(j).avgiprice = buyers(j).
                            avgiprice + buyers(j).items(k).
                            price;
498                 end
499                 buyers(j).avgiprice = buyers(j).
                        avgiprice/length(buyers(j).items);
500             end
501         end
502
503 %% Conversion of buyers and sellers
504         % Change all the buyers that do not have
                enough money (based on the avg
505         % selling price) and make them sellers.
                Collectors do not become
506         % sellers, as they don't want to sell.
507         k = 0; %k indicates the amount of buyers that
                have to be deleted
508         svindex = []; %Saves the indices that have to
                be deleted
509         nsell = length(sellers);
510         nbuy = length(buyers);
511         for j=1:nbuy
512             if (buyers(j).nitems > 0 && buyers(j).mode
                    == 4 && buyers(j).avgiprice > 1.1*
                    avgsoldprice(i))
513                 k = k + 1;
514                 sellers(nsell+k).money = buyers(j).
                        money;
515                 sellers(nsell+k).socstat = buyers(j).
                        socstat;
```

```
516             sellers(nsell+k).nitems = buyers(j).
                  nitems;
517             sellers(nsell+k).gain = buyers(j).gain;
518             sellers(nsell+k).bprice = buyers(j).
                  bprice; %This is so sellers remember
                  the price they bought the item for
519             sellers(nsell+k).items = buyers(j).
                  items;
520             for h=1:buyers(j).nitems
521                 sellers(nsell+k).items(h).sold = 0;
522             end
523             sellers(nsell+k).mode = buyers(j).mode;
524             sellers(nsell+k).initmoney = buyers(j).
                  initmoney;
525             sellers(nsell+k).bsoc = buyers(j).bsoc;
526             sellers(nsell+k).bdes = buyers(j).bdes;
527             sellers(nsell+k).sold = 0;
528             svindex(k) = j; %Store the index of the
                    buyer that has to be deleted
529         end
530         if (buyers(j).money < avgsoldprice(i)*1.5
              && buyers(j).nitems > 0 && buyers(j).mode
               == 2) || (buyers(j).mode == 2 && rand()
              < 0.2 && ~isempty(buyers(j).items))
531             k = k + 1;
532             sellers(nsell+k).money = buyers(j).
                  money;
533             sellers(nsell+k).socstat = buyers(j).
                  socstat;
534             sellers(nsell+k).nitems = buyers(j).
                  nitems;
```

```
535             sellers(nsell+k).gain = buyers(j).gain;
536             sellers(nsell+k).bprice = buyers(j).
                  bprice; %This is so sellers remember
                  the price they bought the item for
537             sellers(nsell+k).items = buyers(j).
                  items;
538             for h=1:buyers(j).nitems
539                 sellers(nsell+k).items(h).sold = 0;
540             end
541             sellers(nsell+k).mode = buyers(j).mode;
542             sellers(nsell+k).initmoney = buyers(j).
                  initmoney;
543             sellers(nsell+k).bsoc = buyers(j).bsoc;
544             sellers(nsell+k).bdes = buyers(j).bdes;
545             sellers(nsell+k).sold = 0;
546             svindex(k) = j; %Store the index of the
                    buyer that has to be deleted
547         end
548     end
549
550     for j=1:k
551         h = svindex(k-j+1);
552         buyers(h) = [];
553     end
554
555     % Now check if any of the sellers who are not
          a setter has no items and
556     % make them buyers. nsell is updated with the
          new amount of sellers,
557     % but it should not change the buyers who just
          became sellers, as they
```

```
558     % would have items, if everything worked
          correctly
559     k = 0;
560     svindex = [];
561     nsell = length(sellers);
562     nbuy = length(buyers);
563     for j=1:nsell
564         if sellers(j).nitems == 0 && sellers(j).
              mode ~= 1
565             k = k + 1;
566             buyers(nbuy+k).money = sellers(j).money;
567             buyers(nbuy+k).nitems = sellers(j).
                  nitems;
568             buyers(nbuy+k).socstat = sellers(j).
                  socstat;
569             buyers(nbuy+k).mode = sellers(j).mode;
570             buyers(nbuy+k).gain = sellers(j).gain;
571             buyers(nbuy+k).items = sellers(j).items;
572             buyers(nbuy+k).initmoney = sellers(j).
                  initmoney;
573             buyers(nbuy+k).bought = 0;
574             buyers(nbuy+k).bdes = sellers(j).bdes;
575             buyers(nbuy+k).bprice = price*normrnd
                  (1.01, sigma);
576             if sellers(j).mode == 2 %The seller is a
                  socialitee
577                 buyers(nbuy+k).desire = rand()
                      *30+70;
578
579             end
580             if sellers(j).mode == 4 %The seller is a
```

```
                collector
581             buyers(nbuy+k).desire = rand()
                    *20+50;
582         end
583         buyers(nbuy+k).bsoc = sellers(j).bsoc;
584         svindex(k) = j;
585       end
586     end
587     for j=1:k
588       h = svindex(k-j+1);
589       sellers(h) = [];
590     end
591     nbuy = nbuy + k;
592     nsell = nsell - k;
593
594   for j=1:nbuy
595     if buyers(j).bought == 0
596       buyers(j).bprice = buyers(j).bprice +
            normrnd(highp*buyers(j).desire, 90)/50;
597     else
598       buyers(j).bprice = buyers(j).bprice -
            normrnd(lowp/buyers(j).desire, 0.1)*50;
599     end
600   end
601
602   for j=1:nbuy
603     buyers(j).bought = 0; %Restart the bought
          flag for the next iteration
604   end
605   for j=1:nsell
606     sellers(j).sold = 0; % Restart the sold flag
```

```
        for the next iteration
607     end
608     % Check that at least one seller has items to
           sell & at least one buyer
609     % has money to buy
610
611      % Give some money to the people that don't
            have enough money, as if they
612      % earned money in their jobs
613
614      for j=1:length(buyers)
615          if buyers(j).money < price*2 && buyers(j).
               bought == 0
616              buyers(j).money = buyers(j).money + 120;
617          end
618      end
619
620     %Check if an seller is ready to leave the game
           with the same procedure
621      if ~isempty(sellers) && ~isempty(buyers)
622          buypos = 0;
623          sellpos = 0;
624              for j=1:length(sellers)
625              if sellers(j).nitems > 0
626                  sellpos = sellpos + 1;
627              end
628          end
629          for j=1:nbuy
630              if buyers(j).money > 0
631                  buypos = buypos + 1;
632              end
```

```
633         end
634     end
635
636 %% Updating Shoe Item Stats
637     %In every iteration the social status of the
          shoe is affected by
638     %depretiation and by the vintageness of the
          shoe (brand)
639     %
640     if mod(i, 4) == 0
641                 vin = rand(nbrands, 1)*2 + 2;
642     end
643     for j=1:length(buyers)
644         for k=1:buyers(j).nitems
645             buyers(j).items(k).socstat = buyers(j).
                  items(k).socstat - (rand()+1)*3.5; %
                  The social status of the object is
                  affecteed by depretiation
646             buyers(j).items(k).socstat = buyers(j).
                  items(k).socstat + (rand()+1)*vin(
                  buyers(j).items(k).brand); %The
                  social status is affected by the
                  vintageness of the brand
647         end
648     end
649
650     % Delete the items that have a really low
          social status as nobody is
651     % going to buy them
652     itdel = zeros(1, 2); %his array keeps the
          index of the person and the index of the
```

```
      item tobe removed. First person, then item
653   a = 0;
654   for j=1:length(buyers)
655       for k=1:length(buyers(j).items)
656           if buyers(j).items(k).socstat <= 7
657               a = a + 1;
658               itdel(a, 1) = j;
659               itdel(a, 2) = k;
660           end
661       end
662   end
663   for j=1:a
664       i1 = itdel(end-j+1, 1); %This variable
            keeps the buyers from which the item has
             to be deleted
665       i2 = itdel(end-j+1, 2); %This variable
            keeps the index of the item to be
            deleted
666       buyers(i1).items(i2) = [];
667   end
668   for j=1:length(buyers)
669       buyers(j).nitems = length(buyers(j).items);
670   end
671   for j=1:length(sellers)
672       if sellers(j).mode ~= 1
673           for k=1:sellers(j).nitems
674               sellers(j).items(k).socstat =
                    sellers(j).items(k).socstat - (
                    rand()+1)*3.5; %The social status
                     of the object is affected by
                    depretiation
```

```
675                 sellers(j).items(k).socstat =
                        sellers(j).items(k).socstat + (
                        rand()+1)*vin(sellers(j).items(k)
                        .brand); %The social status of
                        the item is affected by the
                        vintageness of the brand
676             end
677         end
678     end
679     % Delete the items that have a really low
        social status as nobody is
680     % going to buy them
681     itdel = zeros(1, 2); %his array keeps the
        index of the person and the index of the
        item tobe removed. First person, then item
682     a = 0;
683     for j=1:length(sellers)
684         for k=1:length(sellers(j).items)
685             if sellers(j).items(k).socstat <= 7
686                 a = a + 1;
687                 itdel(a, 1) = j;
688                 itdel(a, 2) = k;
689             end
690         end
691     end
692     for j=1:a
693         i1 = itdel(end-j+1, 1); %This variable
            keeps the seller from which the item has
             to be deleted
694         i2 = itdel(end-j+1, 2); %This variable
            keeps the index of the item to be
```

```
                deleted
695             sellers(i1).items(i2) = [];
696         end
697         for j=1:length(sellers)
698             sellers(j).nitems = length(sellers(j).items
                    );
699         end
700
701         %Shift the buyers & the sellers so they
                randomize a little bit
702
703         rndb = randperm(length(buyers));
704         buyers = buyers(rndb);
705         rnds = randperm(length(sellers));
706         sellers = sellers(rnds);
707 %           buyers = circshift(buyers, 100);
708 %           sellers = circshift(sellers, 100);
709
710         nbuy = length(buyers);
711         nsell = length(sellers);
712
713 %% Plotting Useful Parameters
714         figure (1);
715         hold off;
716         plot(iter, avg(:, 1), 'DisplayName', 'Average
                total selling price', 'Linewidth', 1);
717         hold on;
718         drawnow;
719         plot(iter, avg(:, 2), 'DisplayName', '
                Socialitee average buying price', 'Linewidth
                ', 1);
```

```
720     hold on;
721     drawnow;
722     plot(iter, avg(:, 3), 'DisplayName', '
          Collectors average buying price', 'Linewidth
          ', 1);
723     hold on;
724     drawnow;
725     plot(iter, avg(:, 4), 'DisplayName', '
          Profiteers average buying price', 'Linewidth
          ', 1);
726     hold on;
727     drawnow;
728     legend ('Location', 'northwest');
729     title('Average Item Price at Each Time')
730     xlabel('Time')
731     ylabel('Price')
732      figure(2);
733     hold off;
734     for j=1:floor(i/newitem)+1
735         plot(iter, avgt(1:i, j), 'DisplayName',
              strcat('Time ', num2str(j-1)));
736         hold on;
737         drawnow;
738     end
739     legend ('Location', 'northwest');
740     figure(3);
741     hold off;
742     for j=1:(size(avgb, 2))
743         plot(iter, avgb(:, j), 'DisplayName',
              strcat('Brand', num2str(j)));
744         hold on;
```

```
745             drawnow;
746         end
747         legend ('Location', 'northwest');
748     end
749     figure(6);
750     hold off;
751     plot(iter, avgsoldprice, 'DisplayName', 'Average
          transaction price');
752     hold on;
753     legend('Location', 'northwest');
754     gain = zeros(n_prof, 1);
755     c = 0;
756     for i=1:length(buyers)
757         if buyers(i).mode == 4
758             c = c + 1;
759             gain(c) = buyers(i).gain + buyers(i).
                  nitems*avg(end, 1);
760         end
761     end
762     for i=1:length(sellers)
763         if sellers(i).mode == 4
764             c = c + 1;
765             gain(c) = sellers(i).gain + sellers(i).
                  nitems*avg(end, 1);
766         end
767     end
768     figure(7);
769     area(gain);
770     xlim([0 n_prof]);
771     xlabel('Profiteers')
772     ylabel('Net Profit')
```

```
773 title('The End Profit of Each Profiteer');
774 figure(5);
775 area(gain);
776 xlim([0 n_prof]);
777 figure(6);
778 subplot(2, 1, 1);
779     hold off;
780     plot(iter, avg(:, 1), 'DisplayName', 'Average
        total selling price', 'Linewidth', 1);
781     hold on;
782     drawnow;
783     plot(iter, avg(:, 2), 'DisplayName', '
        Socialitee average buying price', 'Linewidth
        ', 1);
784     hold on;
785     drawnow;
786     plot(iter, avg(:, 3), 'DisplayName', '
        Collectors average buying price', 'Linewidth
        ', 1);
787     hold on;
788     drawnow;
789     plot(iter, avg(:, 4), 'DisplayName', '
        Profiteers average buying price', 'Linewidth
        ', 1);
790     hold on;
791     drawnow;
792     ylabel('Price [Currency Units]');
793     legend;
794 subplot(2, 1, 2);
795     plot(iter, ntrans, 'DisplayName', 'Number of
        transactions');
```

```
796         ylabel('Transaction');
797         xlabel('Time [Days]');
798 end
```