Modelling Economic Behaviour in the Car Industry using Agent-Based Techniques

Benjamin Ang, Michael Deekimcheng, Ellyn Lee, Jaekob Pimentel
May 24, 2022

Ateneo de Manila University

Section I: Introduction

Because of the improvements in human life quality with the advancements in technology in the last decades, the automobile industry has been a thriving sector. In 2020, the US automobile industry sold around 14,471,800 cars and light truck vehicles. In 2021, the total value generated by the industry is $82.6 billion dollars [1]. Even though the industry was hit hard by Covid-19, it has recovered sharply. After the sales dropped by more than 50% throughout the world in the second quarter of 2020, the third quarter of 2020 through the first quarter of 2021 saw a rapid increase in the levels of production [2].

The fierce competition in the industry requires an analysis of the purchasing behaviour of its customers. However, the complexity of purchasing behaviour and the abundance of choices make quantitative analysis difficult. Traditional research, which focuses on equilibrium-based mathematical and statistical techniques, cannot take into account the variety of factors in the decision-making process [3]. Case in point, traditional research cannot describe or simulate economic and social factors. Furthermore, more descriptive consumer behaviour phenomena like the decoy effect and word-of-mouth cannot be explained by standard linear models [3]. Because of the inadequacy of previous methods, researchers resorted to analysing consumer behaviour qualitatively, which has its own issues. Thus, a new tool, such as an agent-based model (ABM), is needed to simulate consumer behaviour accurately. An ABM simulates autonomous agents' interactions in a given system.

Therefore, ABM is a crucial tool to gain an edge over competitors in the car industry. We aim to use an ABM to simulate consumers' purchasing behaviour under different circumstances.

Section II: Review of Related Literature & References

Agent-based modelling is a bottom-up approach for understanding systems. It analyzes the system by its autonomous agents that interact with each other. Makoto [4] explains that ABM can be used for markets with consumer behaviour that cannot be predicted by standard linear models because of various factors like strong emotional appeal or peer pressure. Over the last 25 years, there's been a number of published articles applying ABM to consumer theory. Cao [5] studied the effectiveness of advertising. He proposed to consider consumers, advertisement, product, medium, and environment. All of which will be used by our model. Makoto emphasised the role of word-of-mouth and peer pressure on consumer behaviour. Zhang & Zhang [3] demonstrated the decoy effect, which shows the importance of the perception and judgement of product quality. They proposed a motivation function that took into account developments made by research papers before theirs:

$$M_i = (PS_i \times P_i) + (QS_i \times Q_i) + (sus_i \times ad_i) + (ft_i \times infl_i)$$

where M_i stands for the agent's value for a certain market; PS_i is the agent's price sensitivity; P_i is the price of the good; QS_i agent's quality sensitivity; Q_i quality of the good; sus_i is the susceptibility to advertisement; ad_i is the advertisement intensity; ft_i is the following tendency to the influence exerted by other agents; $infl_i$ is the perceived influence exerted by other agents.

$$PS_i = -\alpha^{P_i - P_e} + K,$$
$$QS_i = -\beta^{|Q_i - Q_e|} + L,$$

where α and β are adjustable constants, K and L are socio-economic attributes.

$$sus_i = \theta$$
$$ft_i = \lambda$$

Huiru, Jinhui, Jianying, Huiru, Zhijian, Weisong [6] used this model to study consumer behavior of wine in China. They were able to obtain the parameters by releasing a survey in Beijing. The questionnaire sought to obtain information on consumers' demographic profile and their behaviour/preference for wine. After that, they conducted a face-to-face survey in representative wine retailers.

Zhang & Zheng [7] acknowledged the role of internal and external factors in consumer purchase behaviour. He cites Quareshi [8], who explained that internal factors include customers' habits, preferences, culture, and professional status, while external factors include factors such as commodity quality, price, promotion, and service. He then cites Jueqiong [9], who proved the effect of quality on consumers' willingness to purchase.

Because of those, they decided to use the motivation function of Zhang and Zhang to simulate consumer behaviour. They programmed the motivation function using NetLogo. Since they did not conduct any surveys, they made several simplifying assumptions. They assumed that consumers' income represents all the social consumers' attributes. The simulation distributed the hypothetical consumer agents in different areas. The consumers interact with other agents that are within a certain range. The model assumed that consumers' income followed a normal distribution, while the other parameters followed a random distribution. They also assumed facts about the quality and price of commodities A and B. At the end of the simulation, they were able to show the distinct consumers of A and B.

Other researchers used different methods to simulate consumer behaviour. Chun, Qiu, & Mao [10] proposed ABM to simulate consumer behaviour under website promotions. They built a consumer model, a website model, and a context model. They found that website promotions significantly increased consumer purchases.

Recent studies have taken interest in using ABM to model new product market diffusion. Kangur, Jager, Verbrugge, & Bockarjova [11] used an agent-based model for the diffusion of electric vehicles. They used the STECCAR model and Consumat model. The STECCAR model aims to capture the decision making of consumers on the car they plan to purchase, while the Consumat model combines and connects different decision-making strategies.

Overall, related literature reveal the important aspects and factors to consider when creating an agent-based model. Researchers were already able to develop mathematical models that take into account internal and external factors. The relevant in our industry is the motivation function by Zhang and Zhang [3], which was used by Huiru, Jinhui, Jianying, Huiru, Zhijian, & Weisong [6] and Zhang & Zheng [7]. The selection of some parameters depends on the availability of the data and the characteristics of the industry.

Definitions of the parameters to be used:

- Socio-economic attributes
    - Socio-economic attributes of an agent depend on their social standing, which is measured by education, occupation, and income. According to Jose, Angelo, and Flor [12], owning a car is highly correlated with one's income. The study showed that less than 1% of those in low-income families own a car, while 13% and 62% of middle-income and high-income families own at least one car respectively. Those living in urban areas such as Metro Manila are also more likely to own a car than those living in rural areas.
- Price
    - According to Zhang & Zheng [6], price comes in many forms and performs many functions, it is what must be given for a customer to obtain benefits offered by the rest of a company's marketing mix. Price plays a direct role in customers' purchase behaviour, especially compared with the price of competitive products in the market.
- the agent's price sensitivity

  - According to Kagan, a writer in Investopedia [13], the price sensitivity of an agent is the degree to which the price affects the behaviour of the agent. It is usually measured in economics by the elasticity of demand– or in other words, the change in demand based on the change in price.
- Quality
  - According to The American Society, Philip and Keller 2012, and Perreault and McCarthy 2014 as cited by Zhang and Zheng [6], quality is the overall characteristic of a product or service in order to cater and satisfy to the (implied) needs of its consumers. According to “Basic Concepts” 2010, as cited in Zhang and Zheng [6], customer satisfaction is directly proportional to quality as higher quality affects higher customer satisfaction. This then affects a customer’s retention and loyalty to the product and/or service. The study also cites multiple surveys which indicate the major influence of the quality of a product/service on the customer’s purchases.
- Quality sensitivity
  - According to Smith [14], quality sensitivity is the degree to which the quality of a product or service influences the consumer's purchase decision.
- The agent's susceptibility parameter to car brand i's advertisement
  - According to Barr and Kellaris [15], susceptibility to advertising (STA) is defined to be the extent individuals use and value commercial messages or advertisements as their basis for consumption.
- The advertising intensity of brand i;
  - According to Marcus [16], advertising intensity is expressed as the ratio of the cost of advertising to the sales revenue.
- The parameter that shows the agent's follower tendency to the influence exerted by other agents regarding brand i;
  - According to Huiru et al. [6], Consumer following susceptibility is the degree their purchase choices are influenced by other consumers.
- The perceived influence exerted by other agents with respect to brand i
  - According to Huiru et al. [6], brand sensitivity is the degree to which the brand of a product or service influences the consumer's purchase decision.

Section III: Simulation and Modelling

An agent-based model will be used to simulate the purchasing behaviour of consumers of cars. We will use the motivation function proposed by Huiru, Jinhui, et al [6],

$$M_i = (-\alpha^{P_i - P_e} + K) \times P_i + (\beta^{|Q_i - Q_e|} + L) \times Q_i + (\theta \times ad_i))$$

The final purchase decision of an agent is based on:

$$max\{M_1, M_2, M_3, ..., M_i\}$$

Each agent is first differentiated by their income, which will define their socioeconomic parameters K and L. The income of car users was obtained from a study by Carlier from Statista [17], which outlined the proportion of car users in a specific income group. The car price P and quality Q are from a dataset by Mohanty [18]. The dataset is composed of two parts: the training dataset and the test dataset. We only used the training dataset because it already had all the necessary headers, which are, “ID”, “Price”, “Levy”, “Manufacturer”, “Model”, “Prod. year”, “Category”, “Leather Interior”, “Fuel type”, “Engine volume”, “Mileage”, “Cylinders”, “Gear box type”, “Drive wheels”, “Doors”, “Wheel”, “Color”, and “Airbags”.

Susceptibility to advertising (θ), and following tendency (λ) were both quantified using a 5 point scale from 1-completely unaffected to 5-completely dependent. The data for susceptibility to advertising was obtained via a study of how car ads affect consumer opinion. The study by Pilon [19] revealed that after showing an advertisement, 5 percent were certain they would choose Jeep and 10 percent said it was very probable. Because of lack of data, we assumed that the distribution is symmetrical, and thus 5 percent would be completely unaffected, 10 percent are a little affected, and 70 percent are averagely affected. The data regarding the following tendency was obtained from a study by Iyengar, Han, and Gupta [20], they found that the social effect is zero for 48 percent, negative for 12 percent, and positive for 40 percent. The intensity of advertising will be an adjustable parameter in the simulation.

Google Sheets was used in order to compute the averages, the expected values, the variances, and the standard deviations.

For the Income, first, we created a table in Sheet 1 where we placed the price ranges on the first column containing the start of the range and second column containing the end of the range. Then, we took the middle of each range and placed it in the third column. We then placed the proportion on the fourth row. In calculating the standard deviation, we first calculated the expected value of each range by getting the product of the middle of the range and the proportion, placing it in the fifth column. We then got the product of the proportion and the square of the middle of the range; we placed this value in the sixth column.We then get the sums of each the fifth and sixth column then placed this sum below the table. The sums were then used to calculate the variance found below the sum of the sixth column. The standard deviation was then calculated by getting the square root of the variance. This was added to the seventh column.

For the consumer's advertising susceptibility and following tendency, we did the same exact process except taking the middle of the range. Instead of calculating for $E(x_i)$ by multiplying the middle and the proportion, we multiplied its value from the 1-5 scale by the proportion. For acceptance of car price, we extracted the frequencies of cars sold within a range. From there, we did the same thing as process 1.

Section IV: Preliminary Results

```python
def setup(self):
    #create agents (Persons)
    nPersons = int(self.p['Population Density'] * (self.p.size**2))
    persons = self.agents = ap.AgentList(self, nPersons)

    #create grid (local area)
    self.city = ap.Grid(self, [self.p.size]*2, track_empty=True)
    self.city.add_agents(persons, random=True, empty=True)
    global parameters
    #Dynamic variable for all persons
    # Condition {0: No Market, 1: Market A, 2: Market B, 3: Market C}
    for customer in self.agents:
        AgentIncome = parameters['Income']['STDEV']*np.random.randn() + parameters['Income']['Mean']

        K = -542*(np.e**-(((AgentIncome-93831.38)/6471)**2)) # socioeconomic parameter
        L = 48.73*(np.e**(0.00002097*AgentIncome)) # socioeconomic parameter

        Price_Sensitivity_A = -parameters['Price Sensitivity']**(parameters['MarketA']['Price']-parameters['Average Market Pr
        Price_A = parameters['MarketA']['Price']

        Quality_Sensitivity_A = parameters['Quality Sensitivity']**np.absolute(parameters['MarketA']['Quality']-parameters['A
        Quality_A = parameters['MarketA']['Quality']

        Price_Sensitivity_B = -parameters['Price Sensitivity']**(parameters['MarketB']['Price']-parameters['Average Market Pr
        Price_B = parameters['MarketB']['Price']

        Quality_Sensitivity_B = parameters['Quality Sensitivity']**np.absolute(parameters['MarketB']['Quality']-parameters['A
        Quality_B = parameters['MarketB']['Quality']

        Price_Sensitivity_C = -parameters['Price Sensitivity']**(parameters['MarketC']['Price']-parameters['Average Market Pr
        Price_C = parameters['MarketC']['Price']

        Quality_Sensitivity_C = parameters['Quality Sensitivity']**np.absolute(parameters['MarketC']['Quality']-parameters['A
        Quality_C = parameters['MarketC']['Quality']

        Advertising_sus_A = 600*(parameters['advertisement susceptibility']['STDEV']*np.random.randn() + parameters['advertis
        Advertising_sus_B = 600*(parameters['advertisement susceptibility']['STDEV']*np.random.randn() + parameters['advertis
        Advertising_sus_C = 600*(parameters['advertisement susceptibility']['STDEV']*np.random.randn() + parameters['advertis

        MA_equation = Price_Sensitivity_A * Price_A + Quality_Sensitivity_A * Quality_A + Advertising_sus_A
        MB_equation = Price_Sensitivity_B * Price_B + Quality_Sensitivity_B * Quality_B + Advertising_sus_B
        MC_equation = Price_Sensitivity_C * Price_C + Quality_Sensitivity_C * Quality_C + Advertising_sus_C

        if max(MA_equation, MB_equation, MC_equation) == MA_equation:
            customer.condition = 1
        elif max(MA_equation, MB_equation, MC_equation) == MB_equation:
            customer.condition = 2
        elif max(MA_equation, MB_equation, MC_equation) == MC_equation:
            customer.condition = 3

    self.timeStep = 0
```

Simulation starts with a grid. Each agent is separated by their income.

The model assumes that every agent decides based on rational thought, which means that agents will choose markets that maximise their utility. The model also assumes that each agent is already part of one market, and will only switch between existing markets. Another note can be made on measuring quality, which assumes that the price and quality would be equally the same. In the long run, if the quality of the product falls behind the expectations of the car, demand will be driven down which either incentivises companies to improve quality, or reduce its price (to match its respective value for quality). If the quality of the product exceeds product expectations, competitors will try to improve the quality of their respective product within its price range to stay competitive. The quality will then normalise in that certain product range.

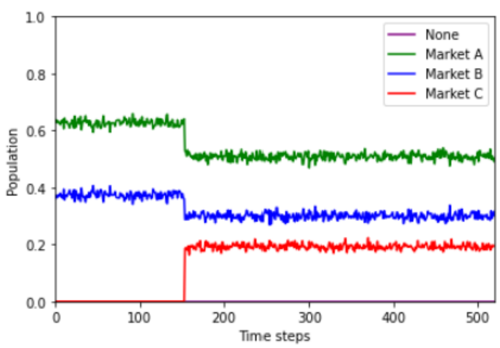
In this setup, agents are created and differentiated by a random distribution, which is normalised by a mean and standard deviation that are based on the user's income data. Each agent also has their corresponding socio-economic parameters for K and L defined by Zhang and Zhang [3]. Other parameters will be specified by the user —price and quality sensitivity, price and quality, advertisement susceptibility, etc. We utilised the equations above to simulate the motivation equation. Using the motivation equation introduced earlier, the agent will enter the market with the highest value for motivation.

```
#Introduces Market C; updates max motivation function for each agent
if self.timeStep > 152:
    if max(MA_equation, MB_equation, MC_equation) == MA_equation:
        customer.condition = 1
    elif max(MA_equation, MB_equation, MC_equation) == MB_equation:
        customer.condition = 2
    elif max(MA_equation, MB_equation, MC_equation) == MC_equation:
        customer.condition = 3
else:
    if max(MA_equation, MB_equation) == MA_equation:
        customer.condition = 1
    elif max(MA_equation, MB_equation) == MB_equation:
        customer.condition = 2
```

From t = 0 to t = 152, the market will only consider the values for Chevrolet and Mercedes. If Chevrolet is the highest value, the agent will be set to condition 1. If Mercedes is the highest value, the agent will be set to condition 2. After t = 152, BMW will be introduced into the pool of markets. This is included in the update step. Then, if BMW is the highest value, the agent will be set to condition 3.

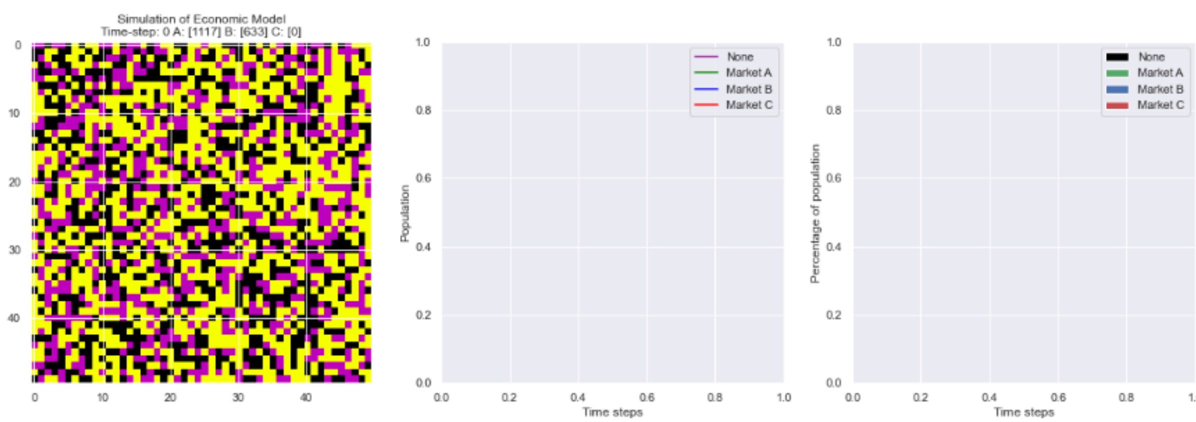
```python
def car_lineplot(data, ax):
    x = data.index.get_level_values('t')
    y = [data[var] for var in ['N', 'A', 'B', 'C']]

    ax.plot(x,y[0], 'purple', label = "None")
    ax.plot(x,y[1], 'green', label = "Market A")
    ax.plot(x,y[2], 'blue', label = "Market B")
    ax.plot(x,y[3], 'red', label = "Market C")

    ax.legend()
    ax.set_xlim(0, max(1, len(x)-1))
    ax.set_ylim(0, 1)
    ax.set_xlabel("Time steps")
    ax.set_ylabel("Population")

model = EconomicModel(parameters)
results = model.run()
fig, ax = plt.subplots()
car_lineplot(results.variables.EconomicModel, ax)
```

```
Completed: 520 steps
Run time: 0:00:18.695965
Simulation finished
```

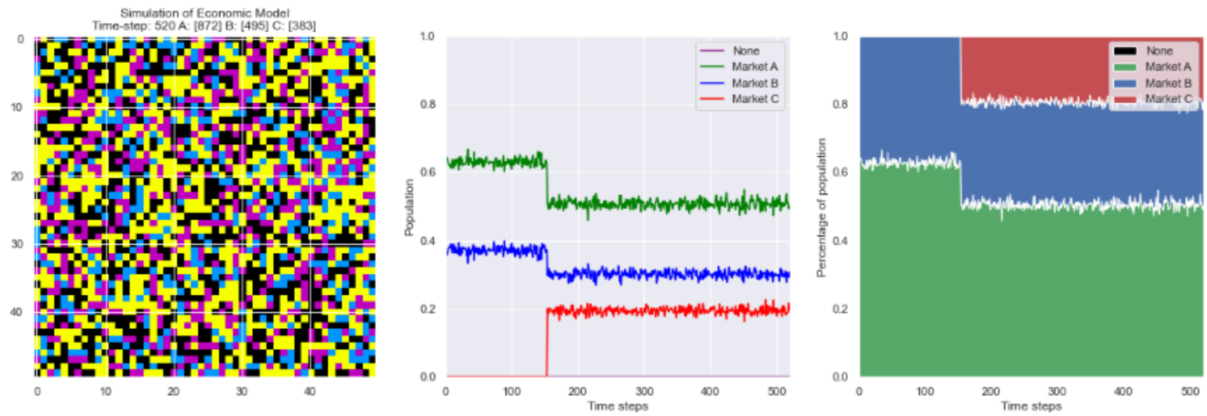


The graph on the right shows the population ratio that are customers to Chevrolet, Mercedes, and BMW. The initial results assume that every agent is already part of any of the markets. The graph on the left shows the decoy effect, a phenomenon found in certain markets that incentivises customers to move from a good choice to a worse one. This often happens due to shifts in consumer perception on product quality.

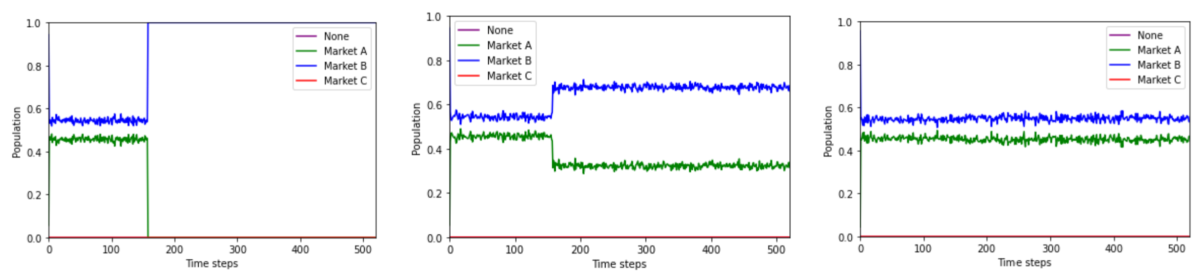
The price of BMW was introduced higher than the average price, but with a lower quality than Mercedes. Initial results show a shift in the market proportions, with a noticeable difference between the proportion decline between Chevrolet and Mercedes.



The three graphs above show the initial results wherein customers are found in either Chevrolet (represented by the yellow pixels), Mercedes (represented by the purple pixels), or BMW (represented by the purple pixels)– which does not have any customers yet as it is introduced later at approximately the 150th time step– which is shown later in the simulation.



The three graphs above show the results of the simulation in 520 time steps wherein customers are found in either Chevrolet (represented by the yellow pixels), Mercedes (represented by the purple pixels), or BMW (represented by the blue pixels). The introduction of BMW, at around the 150th step, shows a decoy effect where the BMW is of lower quality but at a higher price than that of Mercedes. Aside from the external disruption in the market by the entering of a new competitor, the market proportions do not change by significant amounts. Therefore, rational-minded agents should not change decisions unless stimulated by external factors (price change, new competitors, etc.).



Based on the analysis, the car market is highly sensitive to subtle price changes. The graphs mentioned above are theoretical simulations of a 10%, 4% and 1% price change in Chevrolet, respectively. For a relatively small percentage change in the price, the car market is unresponsive. Consumers do not change their preference quickly even if the market price increases. For a 4% increase in the market price of Chevrolet, there is a noticeable shift in the market preference, heavily favouring the cars made by Mercedes. However, a 10% change in the market price heavily shifts the preference of the entire market. Considering the rational-thinking assumption, consumers are heavily price-motivated, and hence consumers prefer to stick to Mercedes which has a lower cost.

The following graphs above confirm several assumptions made in economic theory, specifically consumer behaviour relative to price change. A 1% increase in the price change does not incentivise consumers to change their preference. This may often come from the difficulty of switching car brands easily, considering that the life-span of one good can last several years. Many external factors outside of price may affect the buying decision of several consumers, amongst which include quality factors and the following tendency of buyers [22].

The theoretical simulation follows the simplifying assumption that other external factors stay the same. The analysis does not consider the taste and preference of every individual, nor does it consider external trends on social media that may affect the perception of a brand over time. Considering the analysis on price alone, there is an interesting gap made between the graphs of a 4% price increase and a 10% price increase, which imply that price is a strong motivator for decision-making. If the price of Chevrolet consumes more of a buyer's income, they are more inclined to shift their preference. Based on the simulation, it is possible that a 10% price change can affect the preference of the entire population of the simulation.

Section V: Conclusion and Recommendations

The research adapted an agent-based model to simulate consumer behaviour in the car market. Under several conditions and restraints, the researchers tested if the motivation function model follows economic theory, and subsequently identified such effects. The research considered price and quality determination as the primary signals that incentivise consumers to purchase certain brands. The paper primarily focused on analysing how the decoy market can be employed in the car industry. It has been found that introducing a new competitor can shift the preference of those in existing markets. This shift may be due to the perception on the quality of the goods in comparison to the introduction of the poor-quality “decoy”. As the main signal in the market, the paper also analysed how, with the current income distribution, a price change may affect the change in market preference. The paper has found that subtle price changes may influence the preference, especially if such change is greatly affect by one’s income. In the market, a 10% price change can theoretically convince the market to heavily favour the cheaper option. Such drastic change may be a reflection of the income distribution that was analysed during the research.

For future studies, the paper recommends on improving the relationship between the distribution of the income parameter and its relationship with car sales. This can be accomplished by creating a survey with a greater number of people who own different brands of automobiles. Through this, it is possible to create a more accurate dataset that will create a model fit for the local community. Other parameters, including the advertisement susceptibility of an agent, were based on data that was generalised for previous research. Research recommends conducting a greater investigation through surveys and interviews on the relationship between the local consumer and susceptibility to local advertisement.

It is also possible to compare different markets and income brackets. It is possible to consider how markets respond to changes based on their purchasing power. Other studies may consider modelling the elasticity of certain goods. Such models may consider the effect on the change in quantity demanded considering a change in non-price determinants, such as supply shocks and shortages. It is possible that other external stimuli may have drastic effects on certain car markets.

Section VI. References

[1] Sky Ariella, “36 Important US Automotive Industry Statistics [2022]: Facts, Trends, And Projections,” Zippia.com, Apr. 05, 2022. https://www.zippia.com/advice/automotive-industry-statistics/#:~:text=General%20Automotive%20Industry%20Statistics&text=In%202020%2C%20Americans%20bought%20an,the%20United%20States%20in%202020 (accessed May 23, 2022).

[2] R. Hensley, I. Maurer, and Asutosh Padhi, “How the automotive industry is accelerating out of the turn,” McKinsey & Company, Jul. 16, 2021. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/how-the-automotive-industry-is-accelerating-out-of-the-turn (accessed May 23, 2022).

[3] T. Zhang and D. Zhang, “Agent-based simulation of consumer purchase decision-making and the decoy effect,” Journal of Business Research, vol. 60, no. 8, pp. 912–922, 2007.

[4] M. Makoto, “Forecasting hits in the J-Pop market: a practical application of multi-agent simulation in Japan,” *SFI Business Network: Tutorial on Complexity and Agent Based Modeling*, Jan. 2000.

[5] J. Cao, “Evaluation of Advertising Effectiveness Using Agent-Based Modeling and Simulation,” Proceedings of 2nd UK Workshop of SIG on Multi-Agent Systems (UKMAS), 1999.

[6] W. Huiru, S. Jinhui, F. Jianying, F. Huiru, Z. Zhijian, and M. Weisong, “An agent-based modeling and simulation of consumers’ purchase behavior for wine consumption,” *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 843–848, 2018, doi: 10.1016/j.ifacol.2018.08.089. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405896318312059.

[7] N. Zhang and X. Zheng, “Agent-based simulation of consumer purchase behaviour based on quality, Price and promotion,” Enterprise Information Systems, vol. 13, no. 10, pp. 1427–1441, 2019.

[8] T. Quareshi, “Understanding Consumer Perception of Price Quality-value Relationship,” Journal of Advance Research, Ideas and Innovations in Technology, 2017.

[9] L. Jueqiong, “The Effect of Mobile Payment and Perceived Value on Consumers,” 2018.

[10] J. Chun and D. Qiu, “Agent-based Simulation for Consumer Behavior under Website Promotion,” Systems Engineering-Theory and Practice, vol. 34, no. 4, 2014.

[11] A. Kangur, W. Jager, R. Verbrugge, and M. Bockarjova, “An agent-based model for diffusion of electric vehicles,” Journal of Environmental Psychology, vol. 52, pp. 166–182, 2017.

[12] A. Jose, S. Angelo , and J. Flor, “Profile and determinants of the middle-income class in the Philippines,” *Econstor.eu*, 2018, doi: http://hdl.handle.net/10419/211040. [Online]. Available: https://www.econstor.eu/handle/10419/211040.

[13] J.Kagan, “Price Sensitivity: What You Should Know,” Investopedia, 2022. [Online]. Available: https://www.investopedia.com/terms/p/price-sensitivity.asp.

[14] S. Smith, “New Product Pricing in Quality Sensitive Markets on JSTOR,” Jstor.org, 2022. [Online]. Available: https://www.jstor.org/stable/183766.

[15] T. F. Barr and J. J. Kellaris, “Susceptibility to Advertising: an Individual Difference With Implications For the Processing of Persuasive Messages,” ACR North American Advances, vol. NA-27, 2022 [Online]. Available: https://www.acrwebsite.org/volumes/8392/volumes/v27/NA-27.

[16] M. MARCUS, “THE INTENSITY AND EFFECTIVENESS OF ADVERTISING,” Bulletin of the Oxford University Institute of Economics & Statistics, vol. 32, no. 4, pp. 339–345, May 2009, doi: 10.1111/j.1468-0084.1970.mp32004004.x. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0084.1970.mp32004004.x#:~:text=Advertising%20intensityexpressed%20as%20the%20ratio,advertising%2C%20the%20advertising%2Dsales%20ratio.

[17] M. Carlier, “U.S. car owners by income group 2021,” Statista, 2021. https://www.statista.com/statistics/1041177/us-car-owners-by-income-group/

[18] S. K. Mohanty, “Car Prices Dataset,” Kaggle.com, 2021. https://www.kaggle.com/datasets/sidharth178/car-prices-dataset.

[19] A. Pilon, “Campaign of the Week: Jeep Ad Sends Unifying Message,” Aytm.com, 2021. https://aytm.com/blog/jeep-ad/.

[20] R. Iyengar, S. Han, and S. Gupta, “Do Friends Influence Purchases in a Social Network?,” SSRN Electronic Journal, 2009, doi: 10.2139/ssrn.1392172.

Q