Are consumers willing to pay a higher price for more sustainable clothes?

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Sustainable fashion: A statistical analysis of consumers' behaviors by stated choice experiment

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PREFACE

I chose the topic of sustainable fashion consumption for my thesis because it is highly relevant for where I come from. Many Western brands own or rent textile factories in my hometown in Vietnam. Some of their environmental and labor rights practices have caused a lot of controversies. Therefore, I want to study how sustainable brands can better understand their consumers' preferences in order to compete with fast fashion.

This project started in late February 2020. That was when the Covid-19 pandemic began to take over Europe. I needed to work from home for my internship. I could not meet my friends anymore. Even going out for a walk or visiting the supermarket seemed nerve-racking. Planning and executing a thesis project is never easy, and it became even more challenging during this pandemic which caused much stress and anxiety. There were nights when I doubted myself and felt helpless. It seemed as if I were swimming in a dark ocean without seeing the final destination. I kept telling myself that as long as I did not give up and keep swimming, I would reach the shore. I feel really grateful that I, my family and my friends are all healthy during this unprecedented pandemic. I feel lucky to still be able to do my thesis while many other students have to postpone their work due to closure of labs and schools. Despite all these huge changes in my life as well as in the whole world, I still manage to complete this project within 5 months while doing my internship at the same time.

At the midpoint of the project, I needed to make a very significant change to my research method. At first, I wanted to use both rating and choice experiments. However, after consultation with Dr. Eric Molin, I had to drop the rating part because it was not realistic. This experience really helped me to think in a more scientific way. I believe that it is not only useful for the academic world but also for my future career and life.

I want to say thank you to the admission committee and scholarship committee of Management of Technology (MOT) program. They gave me a priceless chance to embark on a 2-year journey that really transformed me academically, professionally and personally. All my lecturers really opened my eyes with their great knowledge in a wide range of fields. I learned to be more tolerant of ambiguity and to appreciate people's different approaches in answering the same question. My classmates in MOT really inspired me. Coming from different backgrounds, all were highly motivated and passionate about switching to this new field of study.

I also had the opportunity to visit Portugal and Lithuania for two short-term exchanges during my study. Studying and living with such diverse groups coming from various countries, despite for only a short time, really broadened my horizons. I realized how different we were in terms of not only appearances but also values and opinions. Sometimes we may feel scared or lonely to be different. However, it is ok to be different. As a matter of fact, everyone's differences contribute to the beauty of our world. Thanks to these experiences, I always remind myself to look at an issue from multiple perspectives, which is very useful for this project. I do hope that my research can provide a "different" look into the topic of sustainable fashion consumption.

ACKNOWLEDGEMENTS

First and foremost, I want to say thank you to my graduation committee for their great support and assistance throughout this project. I am thankful to Prof.dr. Sabine Roeser for her agreement to become the committee chair and her help to find a suitable first supervisor for this thesis. Without Sabine's help, I would not have been able to start the project. Next, I would like to express my great gratitude to Dr. Andrea Gammon, my first supervisor. Andrea has been a wonderful supervisor who did not only give valuable feedbacks regarding the literature and writing but also kept me motivated with several meetings in the last 5 months. Her expertise in sustainability research really inspired me to learn and obtain more knowledge about this topic. In addition, Andrea went the extra mile to assist me in sharing the survey. I am also very grateful for Dr. Eric Molin, my second supervisor. Eric provided me with the most useful and constructive feedbacks regarding the method, data collection, data analysis and results throughout the project. With his expertise in choice modelling, Eric always gave prompt suggestions for me to adjust the method accordingly and saw the areas that I could further improve. Thanks to Eric, I managed to make a very significant but necessary change to my method at the midpoint of this project.

Next, I am truly grateful for all the help from my friends and contacts to distribute the survey. Thanks to them, I managed to collect over 100 responses in a short amount of time. Some of them gave me really useful comments to improve the design of my survey. I also really appreciate all the respondents who took their time to complete my survey. Without their input, this project would never be successful.

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LIST OF ABBREVIATIONS

ASC	Alternative-Specific Constant
BSCI	Business Social Compliance Initiative
COV	Covariance
EU	European Union
IAF	International Apparel Federation
L	Likelihood
LL	Log-Likelihood
LRS	Likelihood Ratio Statistics
MNL	MultiNomial Logit choice model
ML	Mixed Logit/Mixed multinomial Logit choice model
ORRChem	Chemical Risk Reduction Ordinance
REACH	Registration, Evaluation, Authorization and restriction of CHemicals
RI	Relative Importance
ROBO	Research Online Buy Offline
RP	Revealed Preference (also Revealed Choice)
RUM	Random Utility Maximization
SE	Standard Error
SP	Stated Preference (also Stated Choice)
UR	Utility Range
VAR	Variance
WRAP	Worldwide Responsible Accredited Production
WtP	Willingness to Pay

EXECUTIVE SUMMARY

Sustainability can be defined as the balance between three domains: economic, environmental and social development. New market forces and institutional changes since the end of the 20^{th} century have created both opportunities and challenges in the road towards a sustainable future.

Meanwhile, fashion industry seems to go in the opposite direction with several worrying sustainability issues. Fast fashion, which is characterized by cheap price, high volume and fast product cycle, has kept growing rapidly in the past two decades. The manufacturing process, supply chain and consumption pattern of fast fashion impose high risks on the environment. Besides, the utilization of cheap labor in developing countries by Western fashion brands entails great concern about labor rights of sweatshop workers. To tackle the daunting sustainable issues in fashion industry, various nascent firms have utilized novel technologies to transform their production, supply chain, planning and marketing activities. However, the market size of sustainable clothes is still relatively small.

As a matter of fact, consumers are supportive of sustainable clothes, but their positive attitude does not always turn into actual purchasing behavior. Prior research has shown that there is a discrepancy between people's value and their action. The most obvious reason for this gap is that sustainable clothes are usually more expensive, and the benefit of higher sustainability is not enough to compensate for the price premium. Another important factor relevant for fashion industry is the lack of a labelling system, so consumers do not have information about sustainability of different alternatives. In addition, the issue of greenwashing can desensitize people's trust in the information presented on product labels. No studies have used an objective rating system for sustainability attributes and calculated consumers' willingness to pay for improvement in those ratings. My thesis aims to bridge this gap by studying how consumers trade off price against hypothetically constructed ratings of sustainability.

Discrete choice model was chosen as the research method in this project because it is a statistically rigor quantitative method that can estimate the weight of different variables in consumers' choices and subsequently their willingness to pay. It focuses on consumers' purchasing choices, not just their values or concern, so it is expected to better reflect consumers' behaviors in real life. Sustainability was operationalized into two hypothetical ratings on a 4-point scale: one for environmental aspect and one for labor rights aspect. **7 main variables** representing information on clothes labels (price, country of origin, fiber content, washing instruction, drying instruction, environment rating, labor rights rating) and **12 background variables** (including 6 sociodemographic, 3 spending habit and 3 attitudinal variables) were chosen for this project. A stated choice experiment was constructed to collect data from 123 people.

5 out of 7 main variables (price, fiber content, washing instruction, environment rating and labor rights rating) were proved to play a significant role in respondents' choice. Consumers prefer lower price, pure cotton (vs mixed blend) and the option to use washing machine (vs washing by hand). Regarding the environment and labor rights attributes, higher ratings are preferred, and the preference for higher ratings follows the law of diminishing marginal utility. In the final model, **4 background variables** including gender, country of residence, concern about sweatshops and skepticism of eco-labels were shown to moderate the effects of main variables. Women and residents in high-income countries are more sensitive to price. People who are more concerned about sweatshops attach a higher importance to labor rights rating, whereas people who are more skeptical of eco-labels care less about the it. A typical individual in our sample is willing to pay €12 to €36 more for 1-point improvement of either environment rating or labor rights rating. Consequently, sustainable brands can deploy either of the following two strategies to enhance their sales: (1) charge this price premium without losing their market share or (2) keep the same price to gain more customers.

Although this project is conducted mainly from the perspective of fashion companies, it is also important to address the role of government. Without the necessary information about sustainability of each fashion product, consumers have tremendous difficulty in recognizing sustainable choices. Governments need to provide systematic, objective and compulsory sustainability ratings on apparel so that consumers can make their informed decisions.

CHAPTER 1. INTRODUCTION

1.1 WHAT IS SUSTAINABILITY?

1.1.1 The emergence and evolution of sustainability concept

The concern about uncontrolled exploitation of natural resources to support economic growth dates back to the 18th century when governments in Europe realized the accelerating depletion of timber due to overconsumption. Wood was widely used for a wide range of purposes such as construction, fuel, shipbuilding, etc. at that time. As a result, the number of trees cut down started to exceed the number of newly planted ones. In several published essays, scholars stated that the capacity of forests could not sustain the increasing use of wood, and the resource would soon be depleted without proper management. They suggested that landowners should be responsible for planting new trees, ensuring a stable supply of timber over time. At this time sustainability could be understood as replacing consumed resources with newly created ones. These works laid the foundations for forestry management practices, which was the core sustainability issue until the first half of 20th century (Blewitt, 2014).

In the 1960s and 1970s, debates about compromising environmental conservation for economic development attracted international attention, especially after the fragile beauty of the Earth was captured in a photograph from the outer space by the Apollo 17 astronauts in 1972 (The Blue Marble from Apollo 17, 2001). The environmental movement during this period led to the formation of various pressure groups which asked for a higher concern over ecological systems. In 1972, the Club of Rome, a global group of high-profile politicians and scholars published their influential report **The Limits to Growth**, which was a landmark for the use of sustainability concept with the contemporary meaning. Utilizing simulation methods, the report revealed the constraints of natural resources on population growth and economic expansion. Sustainability was coined as the equilibrium between human and ecological systems (Meadows & Club of Rome, 1972).

In 1983, Gro Harlem Brundtland, the former prime minister of Norway, was chosen by the United Nations to lead the World Commission of Environment and Development (WCED). In October 1987, WCED officially released the impactful **Our Common Future,** which was also known as the **Brundtland Report.** The report recognized the immense challenges faced by the world and proposed the necessary legal changes to ensure the survival and welfare of our future generations. The definition of sustainable development in Brundtland Report is still the most widely accepted until today: a development was considered sustainable if it could fulfil our current needs without damaging posterity's capability to satisfy their own needs (WCED, 1987).

While the definition of sustainable development from Brundtland Report involves intergenerational equity (time dimension), Becker (1997) pointed out the importance of also considering intragenerational equity (social and spatial dimensions). Intergenerational equity means that the welfare of future generations should not be compromised by our current actions, whereas intragenerational equity indicates that our decisions need to take the welfare of currently alive people in all locations into account. Intergenerational concept is usually associated with conserving the nature for posterity, whereas intragenerational viewpoint involves both environment and social viewpoints. Only focusing on environmental issues and ignoring social aspects will lead to harmful consequences. For example, wind power is a renewable energy source that can replace fossil fuel and reduce carbon emissions. Nonetheless, without careful consideration of the wellbeing of communities living nearby, installing wind turbines too close to residential areas can cause worrying health issues such as sleep deprivation and negative emotions, etc. (Pedersen & Waye, 2007).

The economic growth has an interdependent relationship with not only the environment but also the society as a whole. For instance, a flourishing economy can generate jobs and improve living conditions, yet it may also be linked to rising inequality (Yao, 1999) and unethical labor practices (LeBaron, 2014) if the regulations are not appropriately established and enforced. Worsening social problems lead to unrest and instability, which in turn affects the economy negatively. An economic policy, design, initiative cannot be sustained if it causes the social aspects to deteriorate.

Therefore, sustainability should be conceptualized as the intersection of three spheres: economic growth, environmental protection and social development. The system is sustainable when three domains co-exist in harmony and do not inflict negative impacts on each other.

Figure 1. Sustainability as the intersection of Economic, Environmental and Social developments. (Calderon, 2019)

1.1.2 The road towards sustainability

In terms of market change, three new marketing realities have been transforming the business landscape considerably since the turn of the 21st century: technology, globalization and social responsibility (Kotler & Keller, 2016). Each of these three transformative forces gives rise to positive sustainability improvements. Technological advances result in more environmentally friendly production methods as well as improve safety and working conditions of the workforce (eg. using machinery in dangerous tasks). Globalization brings about lucrative businesses and new job opportunities for low-income communities. Corporate social responsibility attracts more and more public attention, pressuring unsustainable firms to mend their problems.

However, these emerging market forces also lead to daunting sustainability issues. Low skilled workers can be easily displaced by new technologies. Larger corporations with better technological resources can wipe out the small local businesses from the market. Inadequate design and maintenance of IT systems may cause cybersecurity issues, threatening the data privacy of millions of people. Globalization allows multinational firms to build factories in developing countries where labor regulations are less stringent, leading to labor rights issues. Some brands may pretend to be environmentally and socially responsible without actually becoming more sustainable. This phenomenon is called greenwashing. While continuing to contribute to environmental and social degradation, greenwashing will also erode consumers' trust in sustainable claims on product labels and in advertising (Seele & Gatti, 2017).

In terms of institutional change, since the 1990s, several international and multilateral agreements have been initiated to support the sustainable development movement. The **Earth Summit** in Rio de Janeiro in 1992 released various documents including **Agenda 21**, which suggested a sustainability action plan for both governments and non-governmental organizations from regional to international scale. While the **Earth Summit** and **Agenda 21** cover the overarching sustainability concept, **Kyoto Protocol**, which was introduced in 1997, aims to tackle the specific problem of climate change. However, many countries refused to ratify the original Kyoto treaty as well as the subsequent amendment in 2012 (Blewitt, 2014). The successor to Kyoto Protocol, the **Paris Agreement** was drafted in 2015 and signed in 2016 by 190 countries (United Nations, 2016). Nonetheless, the agreement is not legally binding and does not entails an enforcement mechanism.

In 2015, realizing the exigent need for a systematic guideline on sustainability, the United Nations introduced the 17 **Sustainable Development Goals** (United Nations, 2020), aiming to provide the necessary guide for policy makers to make informed decisions regarding sustainability issues. These 17 goals are supported by well-defined indicators to track the progress of all countries and regions. They covered a variety of aspects from environmental protection to social issues such as poverty, equality, responsible consumption, discrimination, labor abuses, etc. It can be seen that these goals align with the above-mentioned conceptualization of sustainability, which includes economic, environmental and social developments.

Businesses all around the world, no matter whether they are multinational conglomerates or local family-owned firms, have to transform their strategies and operations to adapt to new marketing realities and institutional changes. At first, becoming more sustainable seems to create massive challenges for a wide range of industries. To comply with stricter standards and regulations (OECD, 2016), companies needed to assess the environmental and social impacts of their businesses, adjust their practices as well as invest in new research.

However, the sustainability trend can also be seen as a new opportunity for the corporate world. Governments provide monetary incentives and expertise consultation for more sustainable manufacturing and supply chain (Moffat & Auer, 2006; Saha, 2009). New complementary and enabling technologies, such as renewable energy sources, assist corporations in their transformation process towards sustainability (Shin et al., 2018). Consumers become more and more aware of the environmental and social impacts of their actions (Fraj & Martinez, 2007).

Therefore, a wave of new companies that thrive on their sustainable image have been emerging in the recent years. While some start-ups provide sustainable consultation and solutions for existing corporations, others are built on totally novel sustainable ideas and business models. For example, Tesla builds new car models that run on electric battery instead of petroleum. Bike-sharing applications including Ofo and Mobike encourages the public to use bicycles instead of CO_2-emitting vehicles. Various start-ups produce straws made from agricultural products such as bamboo and coconut fiber in order to replace plastic straws (Wheeler, 2019). Although the road towards sustainability is rough and precarious, all these business innovations are hoped to bring our world a step closer to a more sustainable future.

1.2 SUSTAINABILITY ISSUES OF FAST FASHION

The sustainability trend has steadily transformed the economic landscape, but one industry seems to go in the opposite direction: the fashion world. In the past two decades, a new type of fashion has emerged. They aim to manufacture clothes at the lowest price, then try to sell a huge number of clothes in order to make up for the smaller margin. This type of brands is called **fast fashion** (Hines & Bruce, 2007). The term "fast" arises from their impressive speed of product development and deployment, allowing these brands to release a larger number of collections per year in order to keep up with the latest trends. The biggest brands such as Zara or H&M releases about 20 collections every year (Howland, 2017), much more frequent than the conventional 2 seasons (spring-summer and autumn-winter). Despite fierce competition in the industry, the revenue of fast fashion is predicted to keep growing substantially. The value of fast fashion industry was estimated to be $35 billion in 2018, and is projected to reach $44 billion in 2028 (Handley, 2019). Although fast fashion provides people who have limited budget with the vast amount of up-to-date apparel, it also generates various sustainability issues, which can be classified into two broad groups: environmental and social (labor rights).

1.2.1 Environmental

Fashion industry engenders negative externalities for the environment throughout the product life cycle, from production, shipping, consuming to disposing.

The first issue is **excessive water consumption**. While about 750 million people in the world do not have access to drinking water, 1.2 trillion tons of water is used annually to grow cotton, and to process clothes in factories (Sustain Your Style, 2020). About 10,000 liters of water are required to produce only 1 kilogram of cotton (Leahy, 2015), which is enough drinking water for 1 person in 14 years. Similarly, the amount of water required for dyeing clothes annually is equivalent to 2 million Olympic-sized swimming pools (McFall-Johnsen, 2019).

Next is **chemical use** and the subsequent **water pollution**. Pesticides are used widely for cotton cultivation, whereas other toxic chemicals containing lead, mercury, chromium are required for bleaching, dyeing, cleaning textile in factories. This industry consumes 23% of all chemicals produced globally. Without proper treatment before discharge, these chemicals will pollute the water sources, which will subsequently affect human health and damage agricultural production. Fashion industry accounts for one-fifth of all industrial water pollution worldwide (McFall-Johnsen, 2019).

High demand for fibers and chemical use also leads to **deforestation** and **soil degradation**. The non-profit organization "Sustain Your Syle" (2020) estimated that 70 million trees are cut down annually to produce wood-based fibers such as rayon. 30% of these fibers are made from wood in ancient and endangered forests. Forests may also be destroyed to give land for breeding sheep or growing cotton. Furthermore, overgrazing to feed sheep and goats for wool as well as using pesticides and other chemicals degrade the quality of soil. In Mongolia, 90% of land is on the edge of desertification due to raising cashmere goats (Sustain Your Style, 2020).

Fast fashion is usually produced in developing countries where the main source of electricity is coal. Synthetic fibers such as nylon and polyester are made from petrochemical precursors. Transporting the clothes around the world further increases the carbon footprint. Overall, the fashion industry accounts for 10% of **greenhouse gas emissions** around the world. This number is projected to reach 26% by 2050 (McFall-Johnsen, 2019).

Processing in factories and washing at home release roughly 500,000 tons of **microplastic** to the environment, which is equal to 50 billion bottles because over half of all clothes contain some amount of polyester. (McFall-Johnsen, 2019; Sustain Your Style, 2020). These microscopic plastics get into aquatic organisms, which are consumed by fish, and eventually polluting our food chain.

Last but not least, due to fast fashion's cheap price and continuous update of trend, the consumption of clothes has increased rapidly over the years. During the first 15 years of the 21st century, fashion consumption increased by 60% (McKinsey, 2016). An average consumer in the US bought 53 garments per year in 2016, i.e. about 1 new item every week (Common Objective, 2018). The quality of fast fashion is usually low, and consumers deem them out-of-style very fast, so these clothes are also disposed very quickly. On average, a piece of clothing is worn only 7 times before being discarded (Sustain Your Style, 2020). Each consumer in the US throws away about 35kg of textile waste per year. The overconsumption and fast disposal of garments create a **huge volume of waste materials** that are either dumped in landfills or burnt, generating more toxic fumes (Bick et al., 2018). Every second, clothing trash that can fill up a truck is disposed. Synthetic fibers are not bio-degradable, and they can take up to 200 years to decompose (Sustain Your Style, 2020).

1.2.2 Social

In addition to menacing environmental problems, fast fashion also creates perilous social issues related to labor rights of workers in sweatshops (Kitroeff & Kim, 2017; Meagher, 2020). The term **sweatshop** can be used to describe the workplace in a wide range of industries such as agriculture, automobile, consumer goods manufacturing, etc, but it is mostly associated with the apparel production. The term appeared in 1830-1850 to indicate a workplace where low-skilled workers work under hazardous conditions for excessively long hours but get insufficient wages. Sweatshops became popular due to the emergence of ready-to-wear clothes for people with lower social status such as slaves in the 19th century America (*Sweatshops 1820-1880*, 2017). From the late 19th to early 20th century, the labor rights movements gradually reduced the use of sweatshops. However, it resurged in the 1960s due to expansion of the labor force, a rising global economy, bigger market for ready-to-wear clothes, etc. (*Sweatshops 1940-1997*, 2017). In the second half of the 20th century, many fashion companies gradually moved their sweatshops from developed countries to developing countries where regulations are usually less strict. Majority of fast fashion products are currently manufactured in developing countries such as Bangladesh, Vietnam, India, China (Pavlova, 2018) before being shipped and sold all over the world. The customers in destination countries where the clothes are sold usually do not know about the operational details of the sources, or manufacturing countries, of their products (Shaw et al., 2006).

Workers in these sweatshops often have **unsafe working conditions** and very little protection against working hazards such as toxic chemicals, air-borne microfibers or ergonomic problems. 50 people have died and 5000 have been reported to become sick due to breathing blasted sands in a Turkish jeans factory (Sustain Your Style, 2020). The factory workers for these fashion brands have no insurance, medical check-up or health protection program. The buildings where they work also have ventilation issues as well as do not meet safety standards. For instance, an eight-floor building in Bangladesh, which housed several garment sweatshops for Western brands, collapsed in 2013, killing over 1000 and injuring 2500 people (BBC News, 2013).

Various fast fashion brands have their factories in Asian, African, and Latin American countries where the labor cost is much cheaper than in developed countries (Kates, 2019). The **insufficient wages** for sweatshops workers in manufacturing countries is the reason why fast fashion brand can still make a profit even though their products are cheaper than traditional brands. The workers are usually forced to work for **excessively long hours** with minimum or even no pay. It is common for sweatshop workers to work up to 96 hours per week. If the workers do not obey or leave early, they will be fired from the factory. There are only two choices for them: continue to work under hazardous conditions or lose their job (Sustain Your Style, 2020).

There have also been reports about verbal and physical **abuses**, including sexual harassment towards workers (Hodal, 2018). **Child labor** and **forced labor** are other common problems. In Uzbekistan, over 1 million people including children are forced by the government to harvest cotton every year. In many apparel factories around the globe, workers are **prohibited to form unions** to protect their rights. For instance, only 10% of textile factories in Bangladesh have a union (Sustain Your Style, 2020).

1.3 TECHNOLOGY AS SUSTAINABILITY SOLUTIONS

In response to the sustainability issues of fast fashion, various nascent companies have utilized a wide range of technology to produce more sustainable products.

First, novel materials have been developed and commercialized to replace traditional types of fiber such as cotton, wool, polyester, etc. For example, to produce spider silk without raising spiders, the German firm AMSilk develops genetically engineered bacteria to generate protein molecules, which are then woven into silk fibers. These fibers have similar composition and characteristics to spider silk, which can be used in several products such as shoes or watch straps. The bacteria-based process is more sustainable than growing cotton, breeding cattle or synthesizing polyester because it uses less water and energy, as well as no petrochemical or animal raw material. Meanwhile, a company from the Netherlands called NEFFA has grown fabric from fungi and made prototypes of bags, coats, etc. The resulting fabric does not require weaving, cutting or sewing, so a large amount of energy can be saved (Fernandez, 2020).

Beside creating new materials, biotechnology can also be used to transform the manufacturing process. A German-Israeli company called Algalife uses algae to dye clothes, which eliminates the use of toxic chemical and reduces water pollution. Their production is a circular system without wasting resources. Similarly, Faber Futures, which is based in the United Kingdom, designs a fermentation process to attach dye molecules to fabric by bacteria. The founder of the company claimed that their process uses 500 times less water than the traditional dyeing (Fernandez, 2020).

Next, blockchain can be used to improve transparency of the fashion supply chain. Blockchain is a list of transaction records that are linked by cryptography (The Economist, 2015). Only new records can be added, while old records cannot be modified or deleted. Sellers and consumers will know the full cycle of their clothes: which farm grows the fiber, which factory assembles the garment, how it is transported to the shop, etc. Information about environmental mismanagement or inhumane treatment of workers will be disclosed to the buyers. A research of Fu et al. (2018) demonstrated a framework to apply blockchain in tracking carbon footprint of fashion products.

In terms of planning and marketing, accelerating advances in software engineering, web design and data science provide the infrastructure and platforms for consumers and producers to exchange the required information more effectively, optimizing the production of clothes and reducing waste. To illustrate, the American firm Stitch Fix obtains consumers' input from an online quiz, then utilizes algorithms in their artificial intelligence to recommend the most suitable personalized clothes (Stitch Fix, n.d.). This model prevents producing unsold clothes that will end up in landfills. Similarly, advanced predictive algorithms can predict demand more accurately, avoiding overproduction. Virtual and augmented reality technology can enable customers to virtually try the product when shopping online so that they do not order clothes that poorly suit or fit them in reality (S. Rogers, 2020). According to a survey of KPMG, over half of the respondents stated that artificial intelligence and augmented reality can help them to avoid unnecessary online fashion purchase that needs to be returned or disposed (KPMG, 2019).

It should be noted that most of the sustainable innovations in fashion industry focus on the environmental side. Few technologies (eg. blockchain) are available to tackle the social side of the problem. As discussed in the previous section, environmental and social developments are both crucial to achieve sustainability. Therefore, it is important for fashion brands to also look at the improvement of labor rights in their factories. Otherwise, the industry can never be truly sustainable.

Although the above-mentioned technologies have shown great potential to be commercially viable, sustainable brands still have a long way to go before they can surpass fast fashion. According to a report from McKinsey consulting firm, only 1% of clothes produced in the first half of 2019 were tagged as sustainable (Cheng, 2019). In the top 10 largest fashion markets, only 3-20% of products came from sustainable brands (Kaucic & Lu, 2019). It has been reported that sustainable clothes are sometimes priced too expensive, which is beyond the budget of the young generation who are the main customer segment for environmentally friendly and fairly traded products. Therefore, sustainable fashion has not reached the scale that it should be at (S. Rogers, 2020). In order to succeed in the market, besides adopting technologies to improve their sustainability, sustainable apparel companies also need to know about consumers' willingness to pay for their products so as to strategize their new product development and pricing.

1.4 SUMMARY – BROAD PROBLEM AREA

Despite the trend towards sustainable development, fashion industry is still facing various environmental and social problems, which are detrimental to the planet as well as the workforce. Textile manufacturing processes consume an excessively large amount of resources, then discharge a high amount of pollutants and wastes. Shipping the products across the world to consumers contributes to more carbon emissions. The overconsumption and fast disposal of clothes generate massive volume of trash. Sweatshop workers for fashion brands have to work in hazardous conditions, receive insufficient wage and face unethical treatment.

To resolve the above-mentioned problems, a variety of technologies have been utilized to improve the sustainability of manufacturing processes, supply chain and marketing activities of fashion industry. Biotechnology can be used to create more sustainable materials and greener production of clothes. Blockchain can help to trace the origin of clothes from the sources of fiber to the delivery channels, ensuring that sellers are fully aware of where and how the products are made and transported. IT infrastructure and applications enable companies to exchange information with customers faster and more efficiently, reducing unnecessary waste.

Despite the use of novel technologies to improve sustainability, sustainable apparel still makes up a much smaller market share compared to fast fashion. The barrier separating sustainable brands from success is the consumers. The key question is not how to become sustainable anymore, but how to understand and meet consumers' preferences. The next chapters will systematically address this issue in a scientific approach.

1.5 OUTLINE

Applying the hypothetical-deductive research method, which involves 7 main steps (Sekaran & Bougie, 2016), the outline of the thesis is as follows.

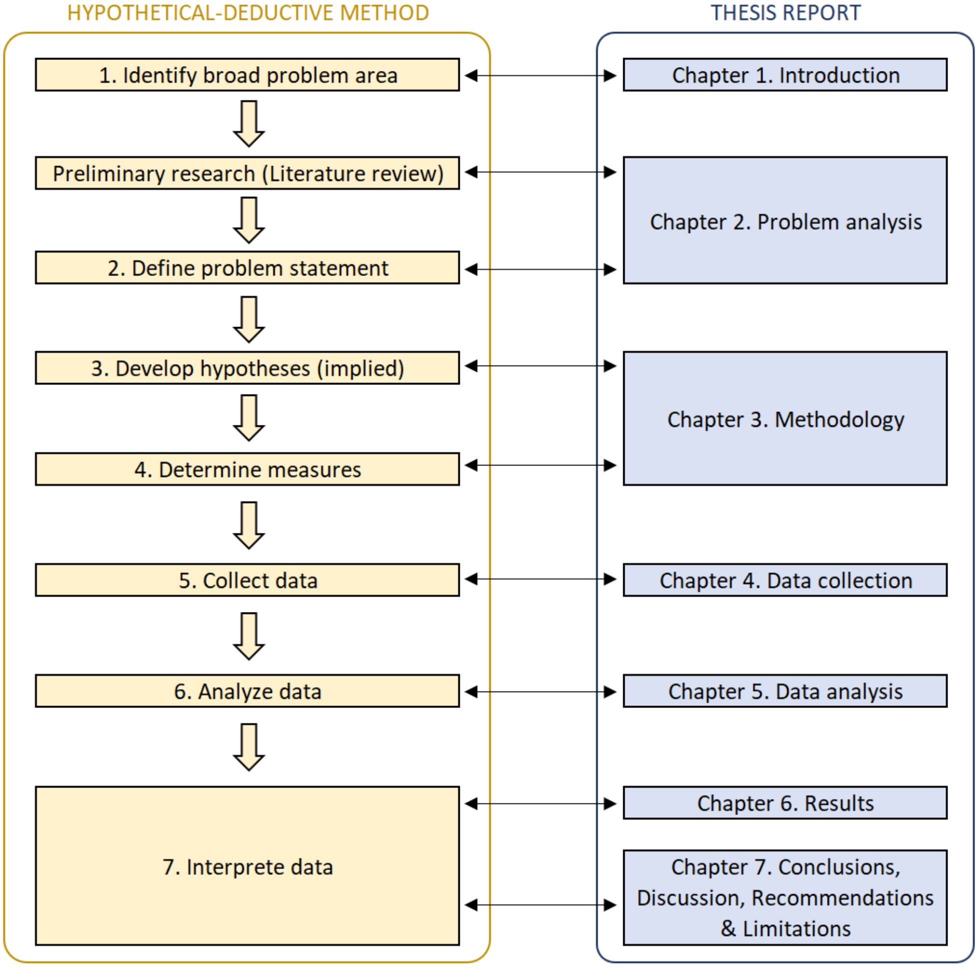


Figure 2. Thesis outline

Chapter 1 (Introduction) provides the background information about sustainability concept, then reveals the broad problem area – sustainability issues in fashion industry as well as discuss the role of technologies in resolving these problems. The chapter concludes that sustainable apparel brands need to understand their customers in order succeed in the competitive fashion industry.

To turn the broad problem into a researchable topic, an intermediate step, which is preliminary research, is required. Literature related to sustainable fashion consumption was examined to identify research gap, and subsequently narrow the problem area down to a research statement, which includes research objective and research questions. Both the literature review and problem statement are covered in **Chapter 2 (Problem analysis)**. This section also discusses the scientific, business and societal relevance of the project.

Next, **Chapter 3 (Methodology)** explains the choice of research method, illustrates how the data will be analyzed and then constructs the experiment to collect the required data. The selection of variables implies the hypotheses of their effects on consumers' choices.

Chapter 4 (Data collection) shows the design and distribution of the survey as well as descriptive characteristics of the sample.

Subsequently, the collected data are analyzed by the chosen research method. **Chapter 5 (Data analysis)** provides the details about this procedure, starting from the simplest to the most accurate model.

The estimation results and explanations are shown in **Chapter 6 (Results).** The best model will be used to calculate willingness to pay and choice probability of consumers, which are useful for sustainable fashion businesses. It will be illustrated how a company can increase their sale after improving their environmental and labor practices.

Finally, **Chapter 7 (Conclusions, Discussion, Recommendations and Limitations)** discusses the significance and limitations of this research. It also recommends future work for businesses and governments in order to make fashion industry more sustainable.

CHAPTER 2. PROBLEM ANALYSIS

2.1 PRIOR RESEARCH & RESEARCH GAP

2.1.1 Supportive attitude towards sustainable fashion

Various literature sources demonstrated consumers' concern about sustainability issues in fashion industry and their support for sustainable apparel (Gam, 2011; Hill & Lee, 2012; Kozar & Hiller Connell, 2013). Overall, consumers have a favorable view of sustainability and sustainable products. In the research of Kagawa (2007) with a sample of nearly 2000 individuals, more than 90% considered themselves supporters of sustainability. Another study of over 300 people by Yan et al. (2012) revealed that respondents associated environmentally friendly fashion products with a positive brand image.

Recent large-scale surveys also confirmed the above findings of the research community. In a 2018 survey with over 5000 people in 5 biggest European markets (Germany, United Kingdom, France, Italy and Spain), about 70-80% of respondents said that it was crucial for apparel brands to address sustainability issues such as environmental protection, climate change, poverty, inequality, etc. (Fashion Revolution, 2018). In another survey in 5 major global cities (Hong Kong, Shanghai, Tokyo, London, and New York) with at least 1000 fashion consumers in each city, 78% of respondents were concerned about environment/pollution/waste issues. On average, 64% claimed that they are supportive of sustainable fashion. This number was expected to further increase in the future because the young generation seemed to be more supportive than the elders in that survey. The age group with the highest support is the youngest one (18-24 years old) with 76%, and the least supporting group is the oldest category (over 55 years old) with 56% (KPMG, 2019).

While the concept of sustainability is usually associated with environmental friendliness, fashion consumers also care about the labor rights aspect of apparel production (Dickson, 1999; Phau et al., 2015). Consumers are supportive of labor rights for fashion workers not only due to concern about sustainability but also because of ethical consideration (Manchiraju & Sadachar, 2014). According to deontological ethics, the morality of an action is based on its conformity to universal rules/laws/duties rather than its consequences. Purchasing from brands that treat their workers poorly is inherently wrong because it gives profit to these unethical businesses, indirectly agreeing with the exploitation of workers. Ignoring labor rights of fashion workers is contradicting to the moral values, causing moral dissonance for ethical consumers. As a matter of fact, the value of social justice, which is related to the attitude towards of sweatshops and exploitation of workers, was found to be an important factor that drove sustainable fashion consumption (Lundblad & Davies, 2016).

Again, consumers' support for both environmental protection and labor rights of workers is consistent with our discussion in chapter 1: both inter-generational and intra-generational equity play an important role in the sustainability of fashion consumption.

2.1.2 Why does supportive attitude not turn into actual purchases?

Despite great support for sustainable apparel, only a minority of consumers actually purchase sustainable clothes. The study of Kozar & Hiller Connell (2013) showed that most fashion consumers did not engage in environmentally friendly and socially responsible purchasing behaviors. In their survey, although the respondents were concerned about environmental and social issues, they had a below-average score for sustainable behavior constructs which measure their likelihood to pay a premium for sustainable choices, checking for sustainability issues before buying, boycotting unsustainable firms, etc. In the survey of the non-profit organization "Fashion Revolution", only one-third of the sample considered environmental and social impacts when they make a purchase (Fashion Revolution, 2018). The study of KPMG also showed a similar pattern. Less than 20% of respondents consistently checked sustainability aspects of clothes during their purchases (KPMG, 2019). This discrepancy between the attitude and the actual behavior is called **attitude-behavior (value-action) gap**, which is a well-documented phenomenon in sustainability studies of various consumer goods (Barr, 2006; Lane & Potter, 2007; Olson, 2013) as well as in other areas such as sustainable dieting (Rocha & Spagnuolo, 2019) and sustainable tourism (Juvan & Dolnicar, 2014). Several reasons for this gap will be discussed below.

Higher price of sustainable options

The theory of innovation diffusion states that innovative products that offer higher benefit than the current reigning ones will spread to the mass market faster and more easily (E. M. Rogers, 2003). Applying that theory to this case, sustainable clothes has not diffused widely yet because its total utility is sometimes lower than that of non-sustainable alternatives. Despite the advantages in terms of environment and labor rights aspects, sustainable clothes are usually more expensive than conventional options, dissuading a large group of consumers (S. Rogers, 2020). It was revealed that only 13% of respondents were willing to buy sustainable fashion at a higher price than normal options (KPMG, 2019). In a study of Norwegian consumers, who are often known to have high concern about sustainability, buyers of sustainable products switched to the less green choices when they faced the trade-off between sustainability and price. This effect was particularly strong when the green alternative offered no other superior qualities besides its sustainability (Olsen, 2013). For products such as cars or TVs, improvement in sustainability also helps to reduce fuel or electricity usage, so at least these monetary benefits can offset the disadvantage of a higher price. For clothes, more sustainable production and supply chain does not offer consumers any direct economic gain. Although a few people may argue that sustainable clothes provide higher quality and durability, the mass population do not have the same view. Only 37% of surveyed respondents associated sustainable clothes with higher quality/more durable (KPMG, 2019). The main benefit obtained from buying sustainable clothes is usually non-monetary, which includes a sense of altruism, compassion and gratitude (Kim et al., 2016). These non-monetary benefits vary significantly for different people. As a result, the disadvantage of higher price may surpass the gain from those positive emotions for an average consumer, who will eventually choose the non-green options. Sustainable fashion brands need to evaluate at which price their products can still have a fair probability of being chosen by consumers. In order to do this, they need to have an accurate estimate of consumers' willingness to pay.

Lack of knowledge and information

Despite their favorable view of sustainability, consumers have tremendous difficulty in recognizing sustainable clothes due to the lack of knowledge and information, which is another reason for the value-action gap.

First, various consumers may not be aware of sustainability issues of the fashion world and the availability of more sustainable alternatives. In a study of Hill & Lee (2012), fashion consumers confessed that they did not have much knowledge about sustainability, and thus were not sure about the impacts of their purchase on the environment. This lack of knowledge may stem from the fact that people generally do not spend much time researching when buying clothes. Shopping for apparel is usually considered a much less important decision (due to lower price and higher purchase frequency) than buying more expensive, less frequent goods such as cars, computers, etc. A study in 2018 revealed that the ROBO (Research Online Buy Offline) score, which indicates how much consumers spend time researching online before actually purchasing the product, was the highest (around 50%) for automotive and electronics products whereas clothing is among the lowest-scoring categories with under 20% (Ellett, 2018).

Research has showed that knowledge about environmental and social issues of fashion production could positively influence purchase behavior (Kozar & Hiller Connell 2013). In contrast, consumers' limited knowledge could be a significant barrier to large-scale sustainable consumption (Connell, 2010; Harris et al., 2016). Therefore, it is important for government and brands to continuously raise public awareness of sustainability by education and marketing campaigns.

Second, even when consumers are knowledgeable about sustainability issues, they still cannot distinguish sustainable clothes from non-sustainable ones due to the lack of information on product labels. It is currently very difficult for an average consumer to obtain reliable information about sustainability policies and practices of fashion brands. A research by Bhaduri & Ha-Brookshire (2011) confirmed that consumers have little access to business practices of fashion companies despite all the advances in information technology. In many cases, consumers could not find the required information to make an environmentally and socially responsible purchasing decision, and had to base their judgement on other characteristics on the label such as country of origin or fiber content (Laitala & Klepp, 2013). A majority of consumers thought that fashion companies should be more transparent about their operations. Nearly 80% of surveyed consumers wanted fashion brands to publish information related to sustainability such as where the material came from, which factories manufactured the product, how much workers were paid, what the company did to reduce environmental impact and enhance labor rights of their workers, etc. (Fashion Revolution, 2018). Although some companies have already put their own sustainability labels on the products, these labels are not consistent across companies, so customers may feel confused and cannot compare them (Janßen & Langen, 2017).

Information is of paramount importance to convince consumers to choose sustainable alternatives (Valor, 2007). In the 2018 survey of KPMG, 65% of respondents said that a labelling system or sustainability score would convince them to purchase sustainable clothes (KPMG, 2019). These results indicate the need for a standardized means to inform fashion customers of environment and labor rights information.

Greenwashing and skepticism

As mentioned in chapter 1, some companies may try to attract more customers by pretending to be sustainable. They attempt to build a sustainable image without actually changing any practices to reduce negative impacts on the environment and the society. This phenomenon is called greenwashing. In fact, greenwashing involves not only lying but also hiding important information from the public. Therefore, a more sophisticated definition of this malpractice is the selective revelation of positive information and concealment of negative information to build an overall favorable brand image (Lyon & Maxwell, 2011).

Seeing the trend towards sustainability as a lucrative business opportunity, an increasing number of brands engaged in this unethical practice (Delmas & Burbano, 2011). There are two main ways a company can lie about their "greenness". First, they can deceive customers into thinking that their products have a better sustainable feature or performance (**product-level**). This is common for cars and electrical appliances. Some typical lies include less fuel or electricity consumption, less emissions, etc. Regarding fashion, brands engaging in greenwashing may claim that their clothes are made of eco-friendly material when they are not in reality. Second, these companies can misrepresent their policies and practices in terms of environmental and social issues (**company-level**). For example, fashion companies can lie about the wage and working hours of their workers in sweatshops. The seriousness ranges from ambiguity (eg. vague language on labels or in advertising) to outright lie (eg. wrong information, fake claims with no proof).

This type of wrongdoing negatively effects consumers' trust in sustainability claims (Chen & Chang, 2013). As a result, consumers become more skeptical of information related to sustainability that they receive from the companies (Lyon & Montgomery, 2015). This issue is particularly detrimental to sustainable fashion. Unlike car or electrical appliances, there are no compulsory classification or labelling requirements for sustainable clothes at the moment. Sustainable brands have to make their own labels with inconsistent claims and messages across different companies. If consumers lose confidence in these claims, sustainable clothes have no other ways to distinguish themselves from conventional clothes. To alleviate the negative influence of greenwashing on green trust, Chen & Change (2013) advised companies to avoid confusing consumers and to reduce consumers' perceived risk related to sustainable choice. To achieve this, it is highly important to adopt a systematic and reliable method of providing sustainability information in the industry.

2.1.3 Quantifying consumers' preferences

Assuming that sustainable apparel firms can provide a trustworthy standardized label on their products, the next step is to understand the effect of the sustainability label on consumers' behaviors. Sustainable fashion brands must quantify the importance of sustainability in consumers' choice and subsequently their willingness to pay for superior sustainability features.

A wide range of research has tried to quantify consumers' likelihood to purchase sustainable clothes. However, the majority of these studies used some descriptive words such as "organic", "sustainable", "eco-friendly", etc. to specify the sustainable clothes (Gam, 2011; Hustvedt & Dickson, 2011; Mostafa, 2007). Therefore, the result was applicable to only the type of clothing which was studied in that research, and could not be generalized to other sustainable clothes. For example, the preference for organic cotton clothing could not be generalized to sustainable wool clothing. In addition, some companies that engage in greenwashing can use these vague terms without any clear definitions. There has been no use of a single objective score that can cover all types of materials, production processes, social practices, etc. in prior literature.

Furthermore, the respondents were usually asked to rate their own purchase intention on a Likert scale. This is the most widely used approach in research of sustainable consumption due to the straightforward design and interpretation of Likert scale. For instance, in the study of Hyllegard et al. (2012), participants were asked to rate their purchase intention on a 7-point scale from "1-Definitely not buying" to "7-Definitely buying" when presented with different labels of sustainable clothes. Similarly, Hustvedt & Dickson (2011) required respondents to use the 7-point scale to estimate how likely they were going to buy organic cotton in the next purchase. However, this approach may not provide a reliable estimate of consumers' true behaviors because people tend to overestimate the behaviors that they deem socially desirable (Chung & Monroe, 2003).

In addition to unreliability, this approach assumed that participants did not have any other alternatives. Even if someone rated that they were "very likely" to purchase sustainable clothes, it did not mean that they would buy it in reality because they might find something else cheaper or suit them better. Olson (2013) has demonstrated the significant effect of comparison with non-green alternatives on the purchase of green products. We cannot ignore these issues because it can invalidate the result of willingness to pay calculation. We need to choose a method that studies consumers' choice instead of subjective judgement.

In conclusion, there are two main issues that prior literature has not addressed. First, an objective score of sustainability is required to provide consumers with necessary information. In this study, a hypothetical classification system will be used to indicate how sustainable a piece of clothing is. Because the sustainability issues of fashion industry can be categorized into two main groups - environment and labor rights, two separate scores are included: one for environment and one for labor rights. They are designed to be on the same scale so that we can test whether consumers combine them into a single score. In the remainder of this report, these two objective scores will be called **Environment rating (Env)** and **Labor rights rating (Labor)**. It is important to note that these ratings are objective evaluation by a trustworthy organization, not subjective perception of customers or the brands. Second, we need a rigor quantitative method that can provide comparison of several attributes (eg. price) between different options instead of asking consumers to judge their purchase intention. Our final goal is to estimate the willingness to pay for improvement in sustainability ratings, which is expected to help sustainable apparel brands with their pricing.

2.2 PROBLEM STATEMENT

2.2.1 Research Objective

Despite great efforts to produce clothes in a more sustainable approach, sustainable fashion brands still make up a relatively small segment of the market. Some possible reasons for the gap between people's supportive attitude and their behaviors includes the expensive price of sustainable alternatives, the lack of sustainability knowledge and information, and skepticism about the provided information. It is highly important for sustainable fashion companies to study consumers' trade-off between price and sustainability so that they can optimize their pricing to reach the mass market.

By using hypothetical ratings for the environment aspect and labor rights aspect of apparel products, this research aims to quantify the importance of price and sustainability in fashion consumers' choices. After that, consumers' willingness to pay for improvement in sustainability will be estimated, providing sustainable companies with quantitative data to price their products appropriately. The research will be done from the perspective of sustainable fashion companies. Only information on product labels is studied in this project. Fashion-related (eg. style, color, etc.), store-related (eg. store design, location, customer service, etc.) and brand-related features (eg. brand image, return policy, promotional programs, etc.) are out of scope.

2.2.2 Research Questions

The main research question of this thesis is:

"How do fashion consumers trade off price against environment rating and labor rights rating when making their purchasing decisions?"

To answer the main research question, three sub-questions are systematically investigated:

1. To what extent do price, environment rating and labor rights rating influence fashion consumers' choices?
2. To what extent do background variables moderate the effects of price, environment rating and labor rights rating on fashion consumers' choices?
3. How much are fashion consumers willing to pay for improvement in environment rating and labor rights rating?

2.3 SCIENTIFIC, BUSINESS AND SOCIETAL RELEVANCE

No prior research has used objective scores of sustainability to measure consumers' preferences for sustainable clothes. In those research, sustainable clothes were tagged with some characteristics such as "organic", "fair trade", "green", "ecological", etc. The results were usually sporadic and applicable for only a certain type of fiber or clothing. Without a standardized system of ratings, it is difficult to generalize their results to other types of sustainable clothes. Second, previous research usually asked the respondents to rate their likelihood to purchase the sustainable options without providing a comparison with conventional non-sustainable alternatives. As a result, there is a potential bias of overestimating consumers' intention to purchase sustainable clothes. This thesis project aims to resolve those issues by using objective classification of sustainability in a choice experiment (discussed in more details in chapter 3). Collecting consumers' choices instead of judgements is expected to better reflect the purchasing behaviors in reality. It also provides an example on how to estimate consumers' willingness to pay for improvement in sustainability ratings.

Sustainable fashion brands can adopt this method to study their consumers' preferences. With a large and representative sample, they can obtain accurate willingness to pay for superior sustainable features compared to conventional choices. Consequently, they can determine how much to charge for their products, enabling them to obtain a larger market share. In the long run, quantitative data collected from consumers' choices can be used to support capital budgeting for their research and development of new products.

From a societal perspective, the results can test the feasibility of sustainable clothes in the market. If the results indicate the presence of a significant willingness to pay for improvement in sustainability attributes, sustainable brands can charge a price premium accordingly and compete with fast fashion. When more sustainable brands become successful in the market, the environment and labor rights of workers can be enhanced. Furthermore, the government may see the need to introduce a compulsory sustainability rating system for all types of clothes. This possibility is not far-fetched considering the fact that several other products such as chemicals and electrical appliances already had a regional or global system of labelling. If the results prove that consumers are not yet willing to pay a higher price for sustainable clothes, brands and governments will know that they need to allocate more efforts for educational and marketing campaigns to increase consumers' awareness.

CHAPTER 3. METHODOLOGY

3.1 METHOD SELECTION

In order to quantify consumers' willingness to pay for sustainable fashion products, we need a quantitative and statistically rigor method, which goes beyond some common approaches used in psychology research such as analyzing correlations between psychological constructs. **Choice model**, which is a mathematical technique for modelling people's decisions, was sufficient for this purpose. Prior research has shown that choice model is the most suitable method to evaluate consumers' willingness to pay for improvements of product features (Breidert et al., 2015), which is crucial for companies' strategic decisions in product development and pricing.

Another method to measure willingness to pay is to ask the consumers directly, but this approach has several problems. For example, can we ask "How much will you pay for an improvement of environment policy?". The first issue is that the questions can be too vague or qualitative in nature. What is the scale used to rate environment policy? How can we measure its improvement? Even if we try to turn the question into a more quantitative form (eg. "How much will you pay for 1-point improvement of environment policy assuming that it is rated from 1 to 7?"), most people do not know what they actually want until the choices are shown to their eyes. Evolution does not program human's brain to make trade-offs explicitly, especially when the choice involves more than two criteria (Wenstøp, 2005). Second, people usually hesitate to provide their true answers regarding sensitive, or taboo, trade-offs such as those related to environment, human rights, religion, fatality, etc. Respondents tend to give socially desirable answers to please the interviewer (Grimm, 2010). Furthermore, judgement is more susceptible to bias than choice. People are likely to overestimate their willingness to pay for improving fashion sustainability when being asked directly. Another pertinent problem is the value-action gap. People may care about sustainable products (***value***), but they do not buy it in reality (***action***). Choice model can alleviate this issue because it mimics real-life purchase scenarios to analyze people's actual behaviors. Finally, economics theories are based on choices, not trade-off judgements. Choice model can help the analysts to calculate product's demand or market share (Small & Rosen, 1981). All things considered, choice model is more appropriate for this thesis.

In choice model, some chosen attributes (independent variables) such as product price, delivery cost, delivery time, etc. are varied, then people's choices (dependent variable) are observed. **Discrete choice model**, a type of choice model in which the choices are in discrete forms, will be used for this thesis. Consumers are asked to choose from a set of two or more discrete alternatives such as ***Buying/Not buying***, or ***Buying a shirt/Buying a dress***, or ***Buying shirt #1/Buying shirt #2***. An example of a discrete choice set is shown below.

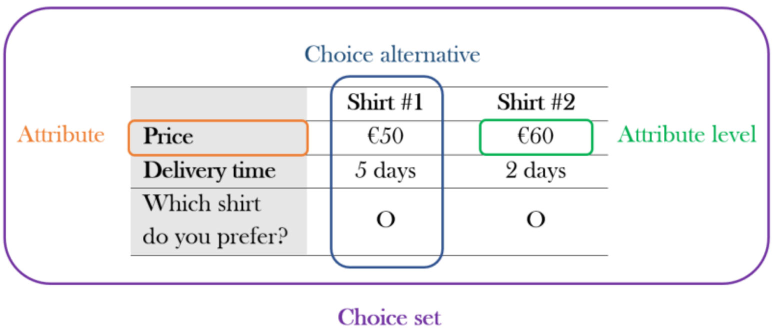


Figure 3. Example of a discrete choice set

The above choice set includes two choice alternatives: ***Shirt #1*** and ***Shirt #2***. There are two attributes (***Price*** and ***Delivery time***) to be compared between the alternatives. The attribute ***Price*** has two attribute levels: ***€50*** and ***€60***, and ***Delivery time*** also has two attribute levels: ***5 days*** and ***2 days***. Based on the respondent's selection of his preferred shirt, we can obtain information about his underlying trade-off between ***Price*** and ***Delivery time***. For instance, if the respondent selects Shirt #2, we know that he is willing to pay at least €10 more to receive the shirt 3 days earlier. Therefore, his willingness to pay for faster delivery time is greater than €10/3 days or €3.33/day. However, because we have only 1 observation, we are not sure whether he is willing to pay €3.5 or €4 or €5 to save 1 day of delivery time (we only know that it is greater than €3.33). If we collect a large enough number of observations with more variation of attribute levels, we can pinpoint his willingness to pay to a narrower range (better precision).

The above discussion demonstrates that discrete choice model is a suitable method for data analysis in this project. The next question is how to collect the required data. There are two main approaches for data collection: Revealed Preference (RP) and Stated Preference (SP), which are compared in the below table. RP asks the respondents for their actual behaviors (real market alternatives), whereas SP asks them to choose from a list of options (hypothetical alternatives).

Table 1. Comparison of data collection methods: Revealed Preference (RP) vs. Stated Preference (SP)

	Revealed Preference (RP) (also called Revealed Choice)	Stated Preference (SP) (also called Stated Choice)
Example	What was the last item of clothing that you bought? How much was it? What was its fiber content?	Which T-shirt do you prefer? - T-shirt #1: €20, 100% cotton - T-shirt #2: €15, 50% cotton
Disadvantages	1. Cannot examine new alternatives (not yet present in the market) 2. Many people may give the same choices (insufficient variation) 3. Only the chosen alternative is known 4. Multicollinearity (correlation among attributes, leading to unreliable estimates) 5. Each respondent makes only one choice, so a large sample size is required.	1. Can lead to potential hypothetical bias (will people actually choose that option in real life?) because of several reasons: - consequence of choices (eg. choosing a more expensive alternative) is not felt by respondents. - in real life, information about all attributes and alternatives is not readily available to people. - in real life, some attributes are hidden. - people are provided with new alternatives and levels that are not available yet in the market.
Advantages	1. High validity because it focuses on what people actually did	1. Can include any new hypothetical alternatives (new attributes and levels beyond current range) 2. Can design any variation of attribute levels and create alternative for rare choice 3. All possible options are known 4. Avoid multicollinearity (correlation among attributes)

		5. Each respondent can make multiple choices, thus requiring a smaller sample size.

Because this research will examine the effects of hypothetical ratings of environment and labor rights (which are not yet present in the market), stated choice is the only option. The stated choice approach also requires a smaller sample size, which is preferred due to time and resource constraints to recruit survey participants. A proper design of stated choice will generate enough variation of attribute levels as well as alleviate the multicollinearity issue. The below figure summarizes the research design for this thesis.

Figure 4. Research design of this thesis

How we design the stated choice experiment to collect data depends on which discrete choice model we use to analyze data (Discrete choice model is a family of several mathematical models, each of which has its own assumptions). Therefore, the next section 3.2 will discuss about which discrete choice models to be used in this project. After that, section 3.3 will demonstrate how the stated choice experiment is constructed to suit the chosen models.

3.2 DISCRETE CHOICE MODELS

Various discrete choice models have been designed and studied extensively. **MultiNomial Logit (MNL)** model is the most popular due to its simple and elegant form as well as straightforward procedure to perform economic appraisal. MNL assumes linear additive contribution of each attribute to the alternative's utility, and relies on maximum likelihood principle to estimate the weights at which the likelihood is the highest. Thanks to the accelerating advance of computing power, other models have been developed to reach a better model fit and thus improve prediction accuracy. Some models are built upon more complex mathematical derivations while others try to incorporate psychology principles into the utility function. **Mixed-Logit (ML)** model allows random distribution of some parameters in order to capture nesting effect, taste heterogeneity or panel effect. **Random Regret Minimization (RRM)** is based on the thought that a loss has a larger effect on utility than a gain. **Taboo Trade-off Aversion (TTOA)** model states that sacrificing a sacred attribute such as fatality against non-sacred attribute such as cost will entail a disutility. MNL and ML are the most suitable to estimate consumers' willingness to pay, so they will be used in this project.

The selection of models will affect the design of choice experiments. MNL and ML models require at least 2 alternatives in each choice set, whereas RRM model requires at least 3 alternatives in each choice set. Because only MNL and ML are used, 2 alternatives per choice set is enough, which will be discussed in 3.3.4.

3.2.1 MultiNomial Logit (MNL) Model

According to Random Utility Maximization (RUM) theory, each alternative is assumed to have a utility, which depends on the attribute levels of all attributes in that alternative. The total utility of alternative i is calculated as follows.

$$U_i = V_i + \varepsilon_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_i$$

where U_i: total utility of alternative i

V_i: systematic utility of alternative i
ε_i: error term of alternative i
β_m: parameter (weight) of attribute m
x_{im}: attribute level of attribute m in alternative i

Condition for alternative i to be chosen is that its total utility is larger than the total utility of all other alternatives j in the choice set:

$$\sum_m \beta_m \cdot x_{im} + \varepsilon_i > \sum_m \beta_m \cdot x_{jm} + \varepsilon_j, \forall j \neq i$$

If the error term is assumed to be extreme value type I with variance $\pi^2/6$, the probability of alternative i being chosen is:

$$P(i) = P\big(V_i + \varepsilon_i > V_j + \varepsilon_j, \forall j \neq i\big) = \frac{\exp(V_i)}{\sum_{j=1..J}\exp(V_j)} = \frac{\exp(\sum_m \beta_m x_{im})}{\sum_{j=1..J}\exp(\sum_m \beta_m x_{jm})}$$

(J is the number of alternatives in each choice set)

The principle of likelihood maximization is used to find the values of parameters at which the likelihood of the dataset is the highest. The likelihood of a model is calculated by multiplying likelihood across all alternatives and all observations. Because each likelihood ranges from 0 to 1, their product after multiplication becomes very close to 0 even for a dataset with moderate size. To enhance computation, natural logarithm of the likelihood is used instead. This is called log-likelihood (LL), which ranges from negative infinity (0% certainty) to 0 (perfect prediction with 100% certainty).

The likelihood and log-likelihood functions of MNL models are as follows:

$$L(\beta) = \prod_n \prod_i P_n(i|\beta)^{y_n(i)}$$

$$LL(\beta) = \ln\big(\prod_n \prod_i P_n(i|\beta)^{y_n(i)}\big) = \sum_n \sum_i y_n(i) \cdot \ln(P_n(i|\beta))$$

where *L(β):* likelihood of the model when the parameter is β
LL(β): log-likelihood of the model when the parameter is β
n: observations
i: alternatives
$P_n(i|\beta)$: likelihood of alternative i given that the parameter is β (for observation n)

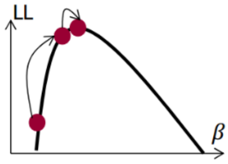
$$y_n(i) = \begin{cases} 1 \text{ if alternative i is chosen (for observation)} \\ 0 \text{ if alternative i is not chosen (for observation n)} \end{cases}$$

From the above formula, the L(0) (likelihood) and LL(0) (log-likelihood) of the initial model when β=0 can be deduced as:

$$L(0) = \prod_n \prod_i P_n(i|0)^{y_n(i)} = \left(\frac{1}{J}\right)^n$$

$$LL(0) = \sum_n \sum_i y_n(i) \cdot \ln(P_n(i|0)) = n \cdot \ln\left(\frac{1}{J}\right)$$

The model is estimated by iteratively finding which value of β gives the highest log-likelihood (making the dataset most likely). Log-likelihood is a concave down curve. We are trying to find the peak (maximum point) of the curve. The most commonly used method is Newton-Raphson method, which includes:



- Taking the first partial derivative will tell us which direction to go along the curve: positive 1st derivative means that we are on the upward part of the curve (likelihood is increasing), so we should increase β more. In contrast, negative 1st derivative means that we are on the downward part of the curve (likelihood is decreasing), so we should decrease β.
- Taking the second partial derivative will tell us whether we should take a small or a big step. A large second derivative means that we are near the peak, so we should take a small step. If the second derivative is small, we can take larger steps.

3.2.2 Panel Mixed Logit (ML) Model

Despite requiring less computing power and providing straightforward economic appraisal, MNL models has an unrealistic assumption of error term distribution, leading to several limitations:

- Ignore correlation between alternatives that have some similar characteristics (**nesting effect**). The correlation stems from variables that the alternatives have in common, but these variables are NOT included in the model. For example, if a consumer considers purchasing from a choice set of 3 alternatives: Shirt #1, Shirt #2 and Dress. The first two alternatives (Shirt #1 and Shirt #2) should have some correlation with each other because they are somewhat similar.
- Ignore difference across people in terms of importance for each attribute (**taste heterogeneity**). For instance, some people are more affected by price than others.
- Ignore correlation among choices made by the same person (**panel effect**). If someone attach very high importance to price in one choice set, he is likely to care a lot about price in other choice sets as well.

In the past, adding these factors to the utility function make it very hard or almost impossible to estimate the model. However, with faster computer processor, it is not an issue anymore. Panel Mixed Logit (ML) model corrects the limitations of MNL model by accounting for the above-mentioned heterogeneities and effects. For ML models, the likelihood is in integral form, which can only be estimated by simulation: taking each draw from the distribution of the parameter, then calculate the corresponding likelihood, and finally take the average. For panel ML models, the unit of observation is the complete set of observations made by the same individual, not each individual observation. The likelihood and log-likelihood of the panel ML models:

$$L(\beta) = \int_{\upsilon_n,\beta_n} \left(\prod_{t=1}^{T} \left(P_{ni}^t \middle| \upsilon_n, \beta_n \right) \cdot f(\upsilon_n, \beta_n) \right) d\upsilon_n d\beta_n$$

$$LL(\beta) = \ln \int_{\upsilon_n,\beta_n} \left(\prod_{t=1}^{T} \left(P_{ni}^t \middle| \upsilon_n, \beta_n \right) \cdot f(\upsilon_n, \beta_n) \right) d\upsilon_n d\beta_n$$

T: the number of observations made by each individual
υ_n is the random error component

The biggest disadvantages of ML model are its more complicated utility function and longer computing time compared to MNL model. However, with the number of attributes in this project, computing time is not a very big problem. The utility function is also not very complicated, so it is still manageable to calculate the willingness to pay and choice probability. Therefore, panel ML model will be built upon MNL models in order to achieve higher accuracy.

3.3 STATED CHOICE EXPERIMENT

A stated choice survey needs to be designed to collect the data for MNL and panel ML models. The stated choice survey includes several choice sets. Each choice set includes 2 or more alternatives with different levels of attributes. We need to construct the context for the choice sets (eg. buying a new piece of clothes for birthday), select the appropriate attributes and their levels, combine these levels properly into choice alternatives, and finally combine alternatives into choice sets.

3.3.1 Context

First, we need to choose what type of clothing to be studied. As the focus of the thesis is on environment and labor rights aspects of apparel products, not preference for different types of clothes, unlabeled alternatives (eg. Jeans #1 vs Jeans #2) is more preferable than labelled alternatives (eg. Jeans vs Dress). Unlabeled means that the alternatives are the same item (Jeans), so we only need a number (1 or 2) to indicate them. In contrast, labeled means that the alternatives are different items (Jeans and Dress), so using only a number is not enough.

We need to choose something that can be worn by anyone (our sample is expected to be very diverse in terms of gender, age, nationality, etc.), so gender-specific products such as dresses or skirts are excluded. That product also needs to have a relatively narrow price range so that we can cover the full price range of that product (or at least the majority of that product on the market) in our survey. Besides, people should have similar assumption about the design of that product (since features such as style or color are not included in the survey), otherwise they will make different assumptions about the design, which may affect their choices. Consequently, the chosen type of product should not have too many variations. Shirt is thus excluded because there are too many different variations (eg. long sleeve vs short sleeve, button-down vs dress shirt, linen vs cotton vs polyester, flannel vs chambray, blouse, etc.) and its price range is quite large. At the end, jeans are chosen because everyone can wear them, their design is fairly homogeneous (most are made of denim fabric with blue/navy/black color), and the price range for the majority of jeans is relatively narrow.

Because only MNL and ML models are estimated, 2 alternatives per choice set (Jeans #1 and Jeans #2) should be sufficient. However, if we include only those 2 alternatives, respondents may feel that they are forced to make the purchase. In real life, consumers can always choose not to buy anything. Therefore, we also need to include an opt-out alternative (not buying), resulting in a 3-alternative choice set:

- Alternative #1: Purchase the pair of jeans #1
- Alternative #2: Purchase the pair of jeans #2
- Alternative #3: Not purchase anything (opt-out option)

Now we encounter another problem. If the above 3 alternatives are presented simultaneously to the respondents, many people may choose the opt-out alternative whenever they find it hard to make a decision. If the opt-out alternative is chosen in too many observations, we will not have enough data to estimate the parameters because the opt-out does not reveal any information about trade-offs. Therefore, it is wise to split each choice set into 2 parts. In the first part, people are asked to select their preferred pair of jeans. Next, in the second part, they are asked whether they will buy that pair of jeans or not.

We also need to create a context with high urgency so that the respondents cannot opt out too easily. As a result, survey respondents will be told to assume that they need to buy a new pair of jeans urgently for a special occasion. We have to choose an occasion when all respondents (both gender, different age groups, etc.) can wear a pair of jeans. For example, wedding is not suitable because many women usually wear dresses to weddings. Job interview is also not appropriate since jeans may be too casual for such a formal meeting. After deliberation, a trip with friends is chosen as the context because a pair of jeans is expected to be suitable for all people during a trip. To further emphasize the necessity of buying this pair of jeans, it is added that the trip will start tomorrow and the group has agreed to take group photos with the denim theme. If the respondents choose to opt out, they will not have any new pairs of jeans for the trip.

Example: Assuming that you are going on a trip with your close friends tomorrow. The group wants to coordinate clothes for group photos, and you agree on the theme of denim. Therefore, you decide to go shopping for a new pair of jeans. You found 2 pair of jeans that you really like.
Part 1: Which pair of jeans do you prefer?
- Jeans #1: €40, 100% cotton, ...
- Jeans #2: €30, 80% cotton, ...

Part 2: Will you buy the pair of jeans that you chose in part 1?
- Yes
- No (you will not have a new pair of jeans for group photos during the trip)

3.3.2 Attributes

Three core pillars of sustainability (Economic growth, Environmental protection, Social development) are operationalized into the following three attributes:

1. **Price:**

The reason why fast fashion manages to flourish despite several issues is mainly due to its low price. It costs more to produce sustainable clothes, so sustainable fashion brands usually need to charge a price premium. In order to survive the fierce competition in fashion industry, sustainable apparel producers need to find the optimal price. Price is directly linked to consumers' purchase decisions, and thus affecting the growth of customer base. In fact, price was stated by fashion consumers as the most important criterion in the study of Chen-Yu & Seock (2002) and in the global survey of KPMG (2019). Various other studies also showed that price influences sustainable fashion purchase (Chan & Wong, 2012; McNeill & Moore, 2015).

2. **Environment rating (Env)** & **3. Labor rights rating (Labor)**:

As discussed previously in chapter 2, concise messages and graphics communicating sustainable practices on clothing tags can positively influence consumers' purchase intentions (Hyllegard et al., 2012). Currently, there is not a compulsory standardized rating for environmental and labor practices on clothes label. Some non-profit organizations such as "Good on you" provide the ratings for a large number of fashion brands (Good On You, n.d.). It includes an overall score, which is subsequently broken down into 3 categories: Planet (environment), People (labor rights) and Animals. Nonetheless, these ratings are not mandated by any governments, so only consumers who really scrutinize sustainability issues of fashion brands will manage to find these ratings online.

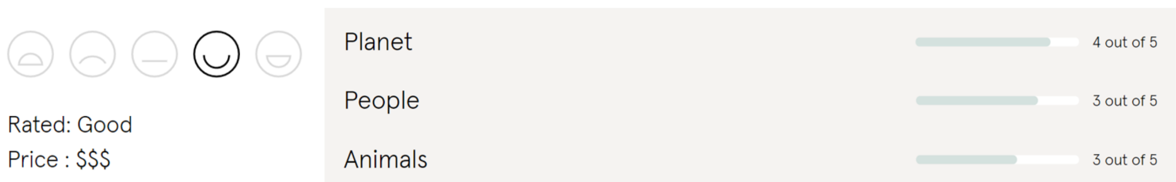


Figure 5. An example of ratings from "Good on you"

Similarly, the EU (European Union) also has an ecolabel for sustainable products, which include apparel (European Commission, 2020). This icon can be put on product labels. However, it is optional, so only a few companies apply to be qualified and use this icon on their products. Besides, it does not give a clear scale like the ratings of "Good on you".

Figure 6. An example of ecolabel by the EU

Therefore, a hypothetical rating will be developed for this study. Survey respondents are asked to assume that the hypothetical rating is objectively given by an international authority, standardized across all companies, and mandated by government to be put on clothing labels. There will be one rating for environment and one rating for labor rights. They will be on the same scale so that we can analyze whether consumers combine them or treat them separately. The detailed design of these hypothetical ratings will be discussed in 3.3.3 (***Attribute levels***).

If only three above-mentioned attributes (Price, Env, Labor) are included in the choice alternatives, respondents will probably overly focus on the ratings, leading to overestimation of their importance. For that reason, other attributes should be put in the choice alternatives as well. We check information currently provided on clothing labels to determine which other attributes are appropriate.

Figure 7. Information on clothing labels

The most commonly found information on clothing labels includes country of origin (eg. Made in USA), fiber content (eg. 100% cotton) and care instructions (washing, drying, ironing, bleaching, etc.). A study of Laitala & Klepp (2013) found that manufacturing country, fiber content and care labels were all related to consumers' evaluation of environmental and ethical impact of clothing purchase. Therefore, they will be included in our study:

4. **Country of Origin (Origin):**

Manufacturing country has been showed to play an important role in shaping the perception and purchase behaviors of fashion consumers. A research of Dickson (1999) showed that American consumers have a much more favorable view about clothes produced locally compared to those from overseas. Furthermore, Godey et al. (2012) found that country of origin significantly affects the purchase intention of apparel consumers in 7 countries.

5. **Fiber content (Fiber):**

Whether the clothes are made from natural (eg. cotton), synthetic (eg. polyester) or blended fiber can affect consumers' preferences (Forsythe & Thomas, 1989). Another study of Choo & Song (2000) showed that over 80% of studied consumers looked at fiber content labels before they make a purchase.

6. **Washing instruction (Wash)** & **7. Drying instruction (Dry):**

More than half of respondents in a survey of Hong & Lee (2007) said that certain information on the care labels could keep them from purchasing a piece of clothing. To maintain parsimony, only washing and drying instructions are chosen for our study because they are present on almost every clothing item. Second, the choice between using washing machine and washing by hand only (as well as between tumble drying and hang drying) is expected to affect people's decisions. Other types of caring instructions such as bleaching, dry cleaning, ironing, etc. are less common or do not have categories that can generate much difference in utility for consumers.

3.3.3 Attribute levels

2 levels are chosen for ***Origin, Wash*** and ***Dry*** attribute:

- ***Origin***: Made overseas vs Made locally.
- ***Wash***: Hand wash only vs Machine washable. The option to use washing machine is expected to be preferred by consumers.
- ***Dry***: Do not tumble dry vs Ok to tumble dry. The option to use tumble dryer is expected to be preferred by consumers.

Regarding ***Origin***, no specific country name is given. Because the respondents in our survey are expected to come from various countries, generic levels such as Made overseas vs Made locally are more appropriate.

The washing and drying symbols currently used on clothes labels provide the inspiration for ***Wash*** and ***Dry*** attribute levels. The levels are chosen in such a way that they are commonly found on most labels and can create a large difference in utility, thus influencing consumers' choices. For example, a level such as "Do not wring" is not chosen because it is rarely seen on clothes label, whereas "Synthetic cycle" and "Gentle/wool wash cycle" are not chosen because they are unlikely to influence the utility and choice probability.

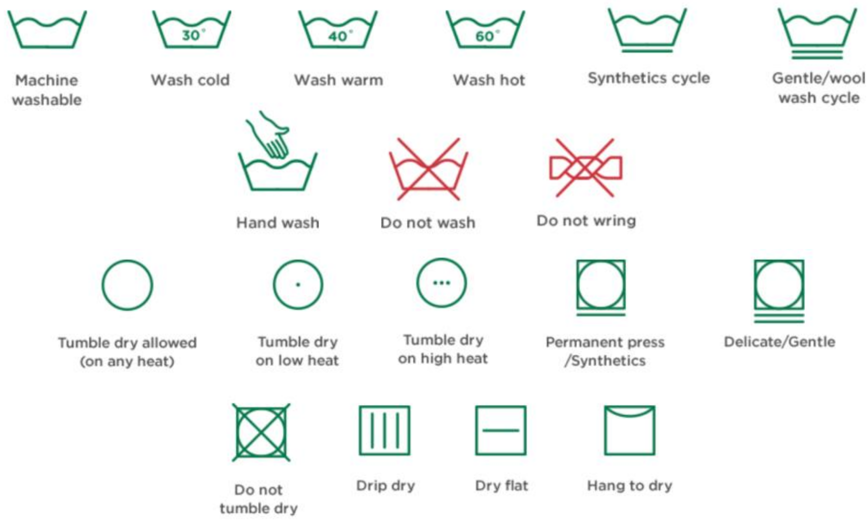


Figure 8. Washing and drying symbols on clothes (Ariel, n.d.)

To keep attribute level balance, it is preferred to have either 2 or 4 levels for the other 4 attributes (***Price, Fiber, Env*** and ***Labor***) as well. To maintain the parsimony, 2 levels should be enough for ***Fiber*** attribute. In contrast, ***Price, Env*** and ***Labor*** attributes, which are the main focus of this study, should have 4 levels because 2 levels do not provide enough variation. Furthermore, having only 2 levels does not allow testing for non-linearity, either. The 4 levels for ***Price, Env*** and ***Labor*** should be equidistant (eg. 10-20-30-40, not 10-25-30-40) so as to maintain orthogonality, which will be discussed in 3.3.4

Regarding ***Fiber*** attribute, jeans is made from denim fabric whose main fiber content is usually cotton. The traditional type of jeans has 100% cotton. Pure cotton jeans provide high comfort and breathability. To modify the properties of jeans, other fibers have been added, resulting in a mixed denim blend. For example, elastane/lycra, a synthetic fiber invented in the 1950s, was added to improve elasticity so that the pair of jeans can fit the body more tightly. Polyester, which is cheaper than cotton, can also be added to reduce the cost (Lorna, 2016). The pure cotton jeans remain the popular choice. A quick check on the websites (Dutch versions) of Zara and H&M, two of the most popular fast fashion brands, reveals that the lowest cotton content in their jeans is 80%. Therefore, 2 levels used for ***Fiber*** attribute will be 100% cotton and 80% cotton.

Next, the price range of Zara and H&M jeans is from about €30 to €60 on their websites for the Netherlands market. It is preferred to cover a wide price range so that the new price after changing environment and labor rights ratings will still fit in this range. However, if the range is too large, ***Price*** will overpower all other attributes. In contrast, if the range is too narrow, ***Price*** will not affect people's choices at all. In addition, the price levels should make sense for the respondents. If the price is too cheap or too expensive, the alternative may not make sense, and respondents will choose randomly and not take the survey seriously anymore. At the end, 4 levels (€30, €40, €50, €60) were chosen to cover the range from €30 to €60.

The levels of environment and labor rights ratings take inspiration from the current labelling system of energy efficiency in the EU (About the Energy Label and Ecodesign, 2020).

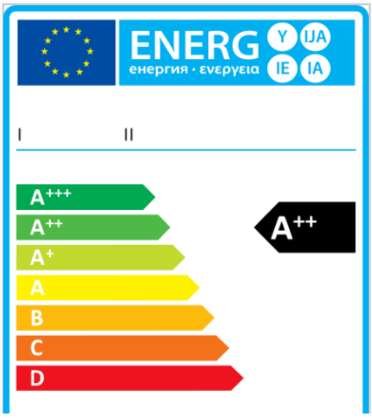


Figure 9. An example of energy efficiency label

In our case, 4 levels are required, so the rating levels will be A-B-C-D accompanied by a number of shaded stars with color ranging from dark green to red. The letter and star ratings are useful for colorblind people. The use of 4 stars in the rating also informs consumers that the rating has 4 levels. All attribute levels are displayed in the below table.

Table 2. List of attribute levels

Attribute	Number of levels	Levels	Coding
Price	4	€30 €40 €50 €60	30 40 50 60
Origin	2	Overseas Local	0 1
Fiber	2	80% cotton + 20% others 100% cotton	0 1
Wash	2	Hand wash only Machine washable	0 1
Dry	2	Do not tumble dry OK to tumble dry	0 1
Environment	4	A ★★★★ B ★★★☆ C ★★☆☆ D ★☆☆☆	4 3 2 1
Labor	4	A ★★★★ B ★★★☆ C ★★☆☆ D ★☆☆☆	4 3 2 1

3.3.4 Choice alternatives and choice sets

There are several types of design to combine different attribute levels into a choice alternative. In full factorial design, all possible combinations are included. Full factorial design allows testing for both main and interaction effects, but it usually results in too many alternatives. In our case, we need 4^3 x 2^4 = 1024 alternatives if we use full factorial design. The second type of design is orthogonal fractional factorial, a fraction of full factorial design in which the correlations among attributes are still zero. Orthogonal fractional factorial design requires a much smaller number of alternatives, but it allows testing for main effects only. To overcome this issue, a foldover (mirror version) can be added to orthogonal fractional design so that we can test for interactions. The third type of design is efficient, which minimizes standard errors of parameters. Efficient design requires prior values of parameter estimates (from literature or pilot survey). Efficient design is better than orthogonal design only when the priors are approximately accurate and the assumed data generation process is correct (MNL is a good approximation for ML, but not panel ML). There are no available priors from literature for our attributes, and panel ML model will be estimated, so orthogonal fractional factorial design was chosen to construct the alternatives.

Because only MNL and ML models are used in this study, each choice set will contain 2 alternatives (If RRM model is required, there should be at least 3 alternatives in each choice set). There are two ways to combine alternatives into choice sets: sequential or simultaneous. Because we use unlabeled alternatives (Jeans #1 and Jeans #2), sequential method is adequate. Simultaneous is suitable for labeled alternatives.

Ngene software (syntax is in Appendix A) was used to generate 16 choice sets. Adding a foldover design (to allow testing for interactions) doubled the number to 32. The design was divided into 2 blocks (16 each) with blocking syntax because it was not reasonable to give each respondent all 32 choice sets at once.

To further reduce the standard error, choice sets with dominant alternatives were removed. Dominant alternative is defined as having no worse attributes than the other alternatives in the same choice set. An example is shown below. Shirt #1 is the dominant alternative because it is cheaper and has shorter delivery time than shirt #2. If all respondents are rational, 100% will choose shirt #1.

	Shirt #1	**Shirt #2**
Price	€50	€60
Delivery time	2 days	4 days
Which shirt do you prefer?	O	O

Figure 10. Example of choice set with dominant alternative

Choice sets with dominant alternative do not give any data about trade-offs, so it is better to eliminate them. Nonetheless, deleting dominant choice sets will introduce some correlations among the attributes because the design is not orthogonal anymore. Correlations should be checked again after removing dominant choice sets to ensure no correlations are significantly high. The attribute level is also not balanced anymore, so it is not possible to estimate 3 parameters for 4-level attributes. Assuming that Price, Env and Labor are continuous, we can still test for deviation from linearity by adding a quadratic component.

In our case, dominance was checked based on the following 5 attributes:

- Price: assuming that lower price is preferred
- Wash: assuming that using washing machine is preferred
- Dry: assuming that using tumble dryer is preferred
- Env: assuming that higher environment rating is preferred
- Labor: assuming that higher labor rights rating is preferred

For Origin and Fiber attributes, we were not sure which level was preferred by the consumers, so they were excluded when checking for dominance. An example of a choice set is shown here. In this example, Jeans #1 is the dominant alternative because all of its attribute levels are at least the same or better than Jeans #2. A rational respondent will always choose Jeans #1.

Characteristics	**Jeans #1**	**Jeans #2**
Price	€ 40	€ 60
Country of origin	Local	Local
Fiber	80% cotton	80% cotton
Washing	Machine washable	Hand wash
Drying	OK to tumble dry	Do not tumble dry
Environment	C ★★☆☆	D ★☆☆☆
Labor rights	A ★★★★	B ★★★☆

Figure 11. A choice set with dominant alternative in this study

After removing choice sets with dominant alternative, 24 choice sets remained. They were in 2 blocks (12 each), which was put in 2 versions of the survey. The correlations among attributes were not too high (all within-alternative correlations are below 0.2). The list of choice sets and correlation tables are put in Appendix A and Appendix B respectively.

3.3.5 Background variables

Some background variables may also affect people's purchase behaviors. These background variables are not varied in the choice sets, but only different across the individuals. The full list of background variables used in this thesis is shown below.

Table 3. List of background variables in this study

Sociodemographic	Spending habit	Attitudinal
• Gender • Age • Education (highest education level) • Income (annual net income) • Nationality (country of citizenship) • Residence (country of residence)	• Clothes (monthly spending on clothes) • JeansFreq (frequency of purchasing jeans) • JeansPay (price usually paid for a pair of jeans)	• ConcernEnv (concern about the environment) • ConcernSwt (concern about sweatshops) • Skepticim (skepticism of eco-labels)

The first group of background variables is sociodemographic. Literature has shown that people's purchase behaviors can be influenced by ***gender*** (Cho et al., 2015; Lee, 2009; Mostafa, 2007), ***age*** (Parment, 2013), ***income*** (Homburg et al., 2010). ***Education*** is also included because Saricam et al. (2017) showed that the level of education is correlated with awareness of sustainable fashion. Several papers researching fashion consumption pattern demonstrated significant differences among consumers from different countries and races (Godey et al., 2012; Shephard et al., 2014; Workman & Lee, 2011). Therefore, it is wise to include ***country of citizenship*** and ***country of residence*** as well.

The second group of background variables is spending habit. It is reasonable to assume that ***monthly budget*** for clothes is likely to affect people's choice. We ask for monthly budget instead of yearly one so that people can provide a more accurate estimate of their spending. Because the chosen clothing item in the survey is a pair of jeans, it is wise to also test for the effect of ***jeans purchase frequency*** and the ***price usually paid*** for this type of clothes.

The final group is attitudinal. Three relevant variables are chosen: ***concern about the environment*** (relevant to the environment rating attribute), ***concern about sweatshops*** (relevant to the labor rights rating attribute) and ***skepticism of eco-labels*** (relevant to the issue of green-washing). Each variable (construct) should be measured by several rating statements. Because only a reasonable number of statements should be given to each survey respondent, about 3-6 statements per construct is appropriate.

The first construct is **environmental concern**. There are several scales that have been used to measure the concern for environment. The most popular one is the New Ecological Paradigm (Anderson, 2012). However, this scale includes statements that are not relevant for sustainable fashion consumption. It is better to use a scale that is specifically tailored for our topic. Abdul-Muhmin (2007) measured several constructs related to environmentally friendly behaviors. Four years later, Gam (2011) applied Abdul-Muhmin's statements into her research in the field of eco-friendly clothing. Gam estimated 3 different constructs related to environmental concern about fashion. The construct with the highest Cronbach's alpha (0.88) and eigenvalue threshold (8.24) among the three also explains the highest amount of variation (41.19%) in the data. Most importantly, it was proved to affect people's intention to purchase environmentally friendly clothing. Therefore, that construct was chosen as a background variable in our study. The chosen construct includes 6 constituent statements.

The second construct is **concern about sweatshops**. Several scales have been adopted to measure concern about human rights issues. For example, Diaz-Veizades et al. (1995) measured the attitude towards social security, civilian constraint, equality and privacy. Nevertheless, none of these are directly related to our topic – labor rights issues in fashion industry. Another research by Dickson (1999) measured concern about sweatshops of American consumers, but he used only 1 statement to ask respondents directly whether they are concerned with issues affecting manufacturing workers, which is not reliable enough. A similar research of Phau et al. (2015) provided 3 potential constructs for concern about sweatshops. The first construct used only 2 statements, which may have reliability issue because each construct in psychology research should have at least 3-4 statements. The second one used 3 statements, but it does not have a significant influence on consumers' intention to not buy sweatshop products. It also does not change their willingness to pay for products made outside sweatshops, so it is excluded. The third construct in Phau's study has the highest Cronbach's alpha, eigenvalue threshold, percentage of explained variance as well as significantly influences consumers' willingness to pay and intention to not purchase sweatshop products. Therefore, the third construct was chosen for our study. It comprises 5 statements.

Finally, we will analyze the effect of a construct called **Skepticism**. It measures the extent to which consumers believe the environmental claims on product labels. This construct was first developed by Mohr et al. (1998). It was later used by Hustvedt & Dickson (2011) in their study about consumers' likelihood to buy organic cotton clothes. In both studies, the construct has good reliability (Cronbach's alpha is 0.79 in Mohr's sample and 0.72 in Hustvedt & Dickson's sample). The construct includes 4 statements.

Table 4. List of statements used to measure 3 attitudinal variables

Concern about environment (ConcernEnv)
1. We should devote some part of our national resources to environmental protection.
2. It is important to me that we try to protect our environment for our future generations.
3. The increasing destruction of the environment is a serious problem.
4. We are not doing enough to protect our environment.
5. It would mean a lot to me if I could contribute to protecting the environment.
6. The environment is one of the most important issues facing the world
Concern about sweatshops (ConcernSwt)
7. Sweatshop issues should be actively discussed and confronted in society.
8. Sweatshop violates labor laws.
9. Sweatshop-based companies damage the interests and rights of sweatshop-free companies.
10. I am concerned about issues affecting sweatshop workers in apparel manufacturing business.
11. Sweatshop damages the the apparel industry.
Skepticism of eco-labels (Skepticism)
12. Most environmental claims made on product labels are true (Reverse coded)
13. Because environmental claims are exaggerated, consumers would be better off if such claims were eliminated
14. Most environmental claims on product labels are intended to mislead rather than inform consumers.
15. I do not believe most environmental claims on product labels.

3.3.6 Conclusion

Our study will analyze the influence of 7 main attributes (Price, Origin, Fiber, Wash, Dry, Env, Labor) and 12 background attributes on the utility of each alternative, which in turn affects the choice of consumers.

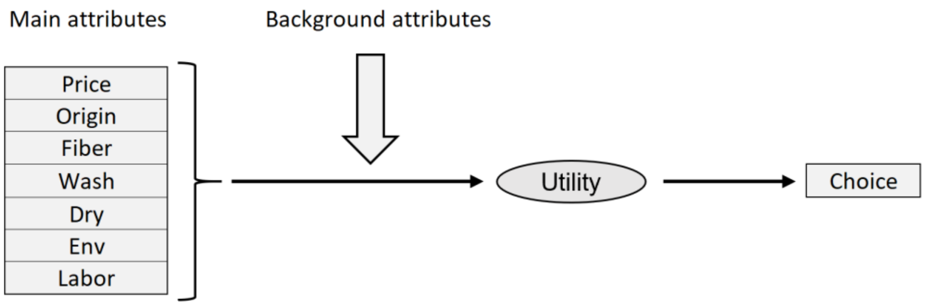


Figure 12. Diagram of variables

CHAPTER 4. DATA COLLECTION

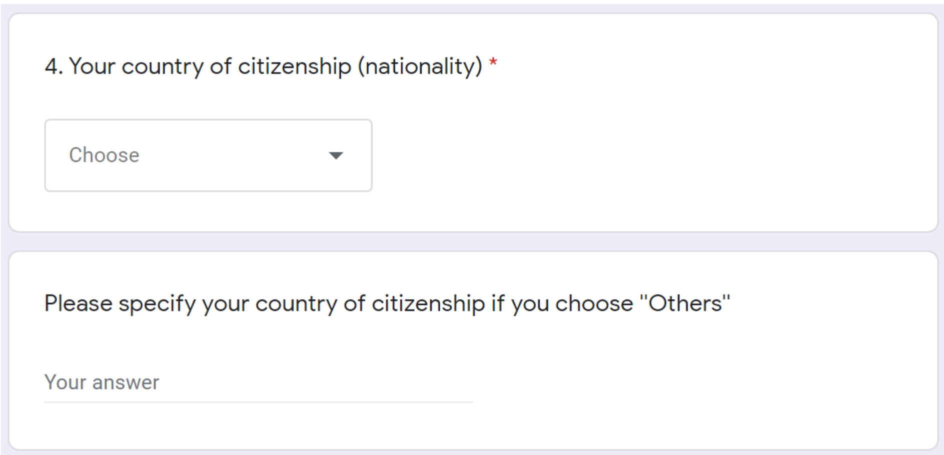
Data will be collected from a survey in the form of an online questionnaire. This chapter will demonstrate how the survey is constructed (4.1) and distributed (4.2), then present the descriptive characteristics of the collected sample (4.3).

4.1 SURVEY DESIGN

The survey was built as an online questionnaire on Google forms with two versions. The survey started with an introduction which stated the research purpose and asks for participants' consent. The body of the survey included 4 main parts. Only the third part (**Choice tasks**) was different between the two versions, while the other parts were the same. The **Attitudinal profile** part was put at the end to avoid influencing respondents' decisions in the **Choice tasks**. If people had been asked about their concern over the environment and sweatshops first, they would have become more alert and given higher importance to environment and labor rights attributes in the **Choice tasks**, leading to validity issues for parameter estimates. The 4 parts of the survey were:

1) Sociodemographic (Gender, Year of Birth, Education level, Country of citizenship, Country of residence, Income)
Dropdown list was used instead of free-text answer to avoid typos or similar names of the same entity. For example, if we had allowed the respondents to type their nationality by themselves, different people would have entered several names of the same country: The Netherlands, Nederland, Holland, Dutch, etc. Some would have used capital letters, whereas others would have typed in lowercase letters. All these differences would have demanded extra time for data cleaning. Therefore, a dropdown list was the better option, facilitating the data analysis process.

However, one disadvantage of using dropdown list was that it could make the survey run much more slowly due to the large number of options. For example, there are nearly 200 sovereign states and territories in the world. To enhance the speed of the survey, we included only 20 nations, each of which was expected to have a high number of respondents based on our circle of contacts, and an extra option "Others" in the dropdown lists for two questions about Country of citizenship and Country of residence. Next, we asked the respondents to specify their country of citizenship/residence if they chose "Others". This solution reduced the time for data cleaning, yet still maintained the interactive speed of the online questionnaire.


4. Your country of citizenship (nationality) *

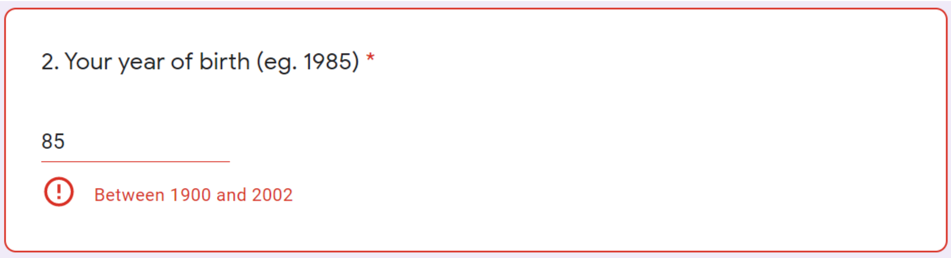
Choose

Please specify your country of citizenship if you choose "Others"

Your answer

Figure 13. Nationality question in survey

For Year of birth, dropdown list was also not used to avoid slowing down the survey. The respondents could enter their answers. However, the only allowed answers were numbers between 1900 and 2002 (to make sure that they were at least 18 years old). This setting ensured that people entered the whole 4-digit year (eg. 1985 instead of only 85) as well as avoided other formats such as dd-mm-yyyy.

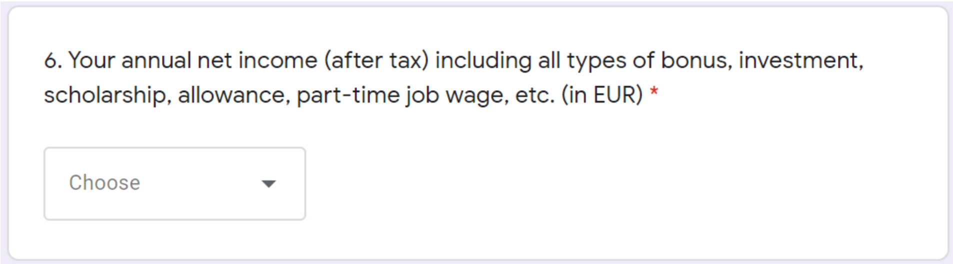

2. Your year of birth (eg. 1985) *

85

Between 1900 and 2002

Figure 14. Year of birth question in survey

Regarding Income, because respondents come from various countries with different tax rules, net income (after tax) was is instead of gross income (before tax) for a better comparison of purchasing power. Second, people have very diverse schemes of holiday allowance and bonus, so asking for information about annual income is more appropriate than monthly income.


6. Your annual net income (after tax) including all types of bonus, investment, scholarship, allowance, part-time job wage, etc. (in EUR) *

Choose

Figure 15. Income question in survey

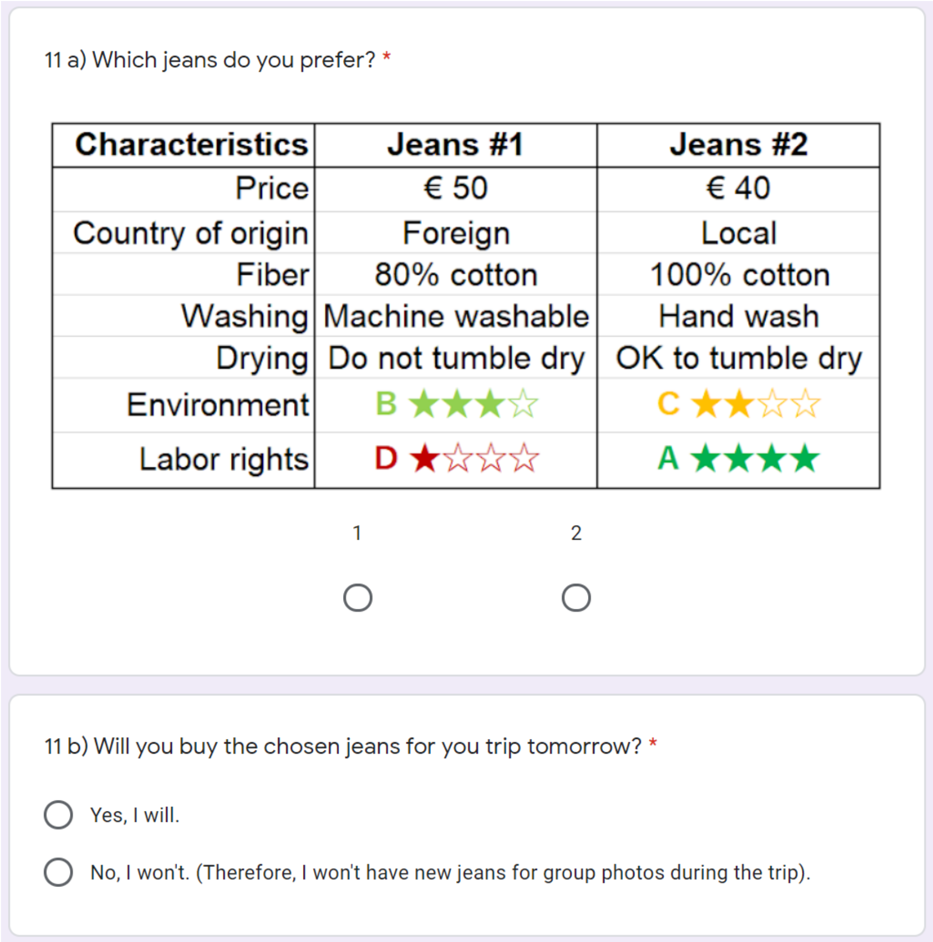
2) Spending habit (How much they spend on clothes per month, How often they buy a pair of jeans, How much they usually pay for a pair of jeans)
Again, respondents could choose answers from the available options in dropdown lists. To cover all possible answers, an open-ended category was added to each question. For example, regarding the monthly spending on clothes, we provided the following options: €0 – €20; €20 – €40; ...; €180 – €200; over €200 (open-ended category).

3) Choice tasks (12 choice sets with 2 sub-questions each)
The respondents were asked to assume that they needed to buy a pair of jeans urgently for group photos with friends during a trip starting the following day. This scenario provided high urgency, preventing people from selecting the opt-out alternative (not buying) without thinking. Respondents would need to deliberate whether to buy the pair of jeans or not. This context was expected to mimic an actual shopping scenario so that consumers' answers would be as close to their real-life decisions as possible.

They were also told that the pair of jeans looked good on them and fitted them well, leaving the information on labels as the only variables to consider. The respondents were provided with brief explanation of the attributes in the choice tasks: Price, Country of origin, Fiber content, Washing and Drying instructions, Environment and Labor rights ratings.

The Environment and Labor rights ratings were presented as official ratings from an international authority, which was required by the government to put on all apparel labels. Because the respondents in the survey came from many countries, an international organization should be used instead of a national or a regional one. IAF (International Apparel Federation) was chosen because it is a long-established organization that has partnerships with about 60 national trade associations and several corporations all around the world. Next, some sustainability issues of the fashion industry were quickly mentioned so that the respondents could understand the basis of these ratings. Examples of environmental issues include carbon emission, use of toxic chemicals, water pollution, waste disposal, lack of recycling, etc., while labor rights issues involve unsafe working conditions, workers' exposure to health hazards, insufficient wage, child labor, abuse and discrimination, etc. Finally, people were reminded to treat the questions as independent scenarios, meaning that the answer to one choice task should not affect another one. 12 choice tasks were then presented. Each task included two sub-questions: first, the respondents needed to indicate their preferred pair of jeans. Second, they needed to decide whether they would buy that pair of jeans or not. An example of one choice task is shown below.

Figure 16. Explanation of environment and labor rights rating in the survey



11 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 50	€ 40
Country of origin	Foreign	Local
Fiber	80% cotton	100% cotton
Washing	Machine washable	Hand wash
Drying	Do not tumble dry	OK to tumble dry
Environment	B ★★★☆	C ★★☆☆
Labor rights	D ★☆☆☆	A ★★★★

1 ○ 2 ○

11 b) Will you buy the chosen jeans for you trip tomorrow? *

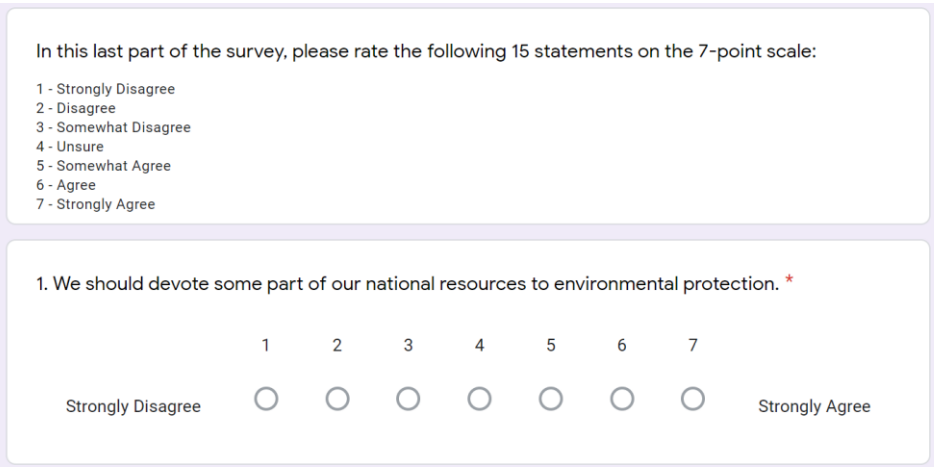
○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

Figure 17. A choice task in the survey

4) Attitudinal profile (15 statements rated on a 7-point scale)

In this part, 15 statements were provided, and the respondents were asked to rate them from 1 (strongly disagree) to 7 (strongly agree).



In this last part of the survey, please rate the following 15 statements on the 7-point scale:

1 - Strongly Disagree
2 - Disagree
3 - Somewhat Disagree
4 - Unsure
5 - Somewhat Agree
6 - Agree
7 - Strongly Agree

1. We should devote some part of our national resources to environmental protection. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Figure 18. Rating scale for attitudinal statements in the survey

Because some participants may not be familiar with the concepts of sweatshop and eco-label, two photos were added to provide some visual context: one depicting an apparel sweatshop and one illustrating a generic eco-label. The photos were chosen such that they did not evoke any strong negative or positive emotions. For example, the sweatshop photo was neutral with no visual clues indicating any potential labor rights problems such as dangerous working conditions, child labor, discrimination or abuse, etc.

Figure 19. Photos of sweatshop and eco-label in the survey

The full survey is shown in Appendix C.

4.2 SURVEY DISTRIBUTION

The two questionnaire versions were randomized and distributed to the researcher's direct contacts and their acquaintances as well as shared on social media platforms. All people who were at least 18 years old and had bought at least a pair of jeans in the last 5 years could participate in the survey. This approach could be seen as convenience sampling, which was a non-probability sampling method. Convenience sampling was chosen because it was fast, readily available, easy to conduct and cost effective. This research is a first step in gauging people's willingness to pay for improvement in sustainability of fast fashion. Therefore, convenience sampling should be sufficient for this purpose.

The survey took approximately 10 minutes and did not require any special technical skills or esoteric domain knowledge to complete. It could be done on either computers or smartphones. In total, 123 people completed our survey. The distribution of two questionnaire versions was fairly even (46% - 54%). If one version had been overly distributed, the correlations between attributes would have become too high, increasing the standard errors and thus reducing the reliability of parameter estimates.

Table 5. Distribution of questionnaire versions

N = 123	Absolute	Relative (%)
Questionnaire version		
Version 1	56	45.5%
Version 2	67	54.5%

4.3 SAMPLE CHARACTERISTICS

This section displays the descriptive statistics of the collected sample. Sociodemographic, Spending habit and Attitudinal profile are shown in 4.3.1, 4.3.2 and 4.3.3 respectively.

4.3.1 Sociodemographic

The distribution according to sociodemographic variables of the collected sample is shown in the below table.

Table 6. Sample characteristics (Sociodemographic)

N = 123	Absolute	Relative (%)
Gender		
Female	74	60.2%
Male	49	39.8%
Age		
19 – 22	14	11.4%
23 – 26	37	30.1%
27 – 30	39	31.7%
31 – 34	14	11.4%
35 – 38	9	7.3%
39 – 63	10	8.1%
Education		
Others	2	1.6%
High school	4	3.3%
Technical/Vocational training	2	1.6%
Bachelor degree	38	30.9%
Master degree	63	51.2%
PhD and above	14	11.4%
Nationality		
The Netherlands	22	17.9%
Other European countries	24	19.5%
Vietnam	40	32.5%
Other Asian countries	24	19.5%
Other regions	13	10.6%
Residence		
The Netherlands	70	56.9%
Other European countries	23	18.7%
Vietnam	12	9.8%
Other Asian countries	7	5.7%
Other regions	11	8.9%
Income		
€0 – €10,000	52	42.3%
€10,000 - €20,000	19	15.4%
€20,000 - €30,000	15	12.2%
€30,000 - €40,000	13	10.6%
€40,000 - €50,000	12	9.8%
€50,000 - €60,000	3	2.4%
€60,000 - €70,000	4	3.3%
€70,000 - €80,000	2	1.6%
€80,000 - €90,000	0	0.0%
€90,000 - €100,000	1	0.8%
Over €100,000	2	1.6%

Even though more women responded to the survey than men, the difference is not too far from a fifty-fifty distribution. This gap may come from the fact that women are usually more interested in fashion (Koca & Koç, 2016; Pentecost & Andrews, 2010) and sustainability topics (Lee, 2009), thus more willing to complete the survey.

The youngest and oldest respondents are 19 and 63 respectively. In the above table, age is grouped in 4-year bins for the range from 19 to 38. The last bin covers the remaining people who are above 38. A quick look at the age and education levels reveals that the majority of respondents are relatively young and highly educated. Nearly three quarters of the sample are 30 years old and below. More than 90% of respondents are currently attending or have completed a tertiary education (roughly 30% with Bachelor degree, 50% with Master degree and 10% with PhD and above). Next, income distribution is positively skewed with over 40% in the lowest category (having an income of less than 10,000 euros a year).

In terms of nationality, Asian countries account for the biggest portion with 50%, while European countries account for 40%. The largest groups are Vietnamese (32%) and Dutch (18%). The distribution of residential country has a different pattern. The number of respondents living in Europe (75%) is five times as many as in Asia (15%), with a large majority residing in the Netherlands (57%). People coming from other regions (North and South America, Africa, Oceania) make up only about 10% for both nationality and residence in the sample.

4.3.2 Spending habit

Table 7. Sample characteristics (Spending habit)

N = 123	Absolute	Relative (%)
Clothes (Monthly spending on clothes)		
€0 – €20	45	36.6%
€20 – €40	36	29.3%
€40 – €60	13	10.6%
€60 – €80	10	8.1%
€80 – €100	8	6.5%
€100 – €120	6	4.9%
€120 – €140	2	1.6%
€140 – €160	0	0.0%
€160 – €180	0	0.0%
€180 – €200	2	1.6%
Over €200	1	0.8%
JeansFreq (How often the person buys a pair of jeans)		
1 pair every 4-5 years	9	7.3%
1 pair every 2-3 years	36	29.3%
1-2 pairs a year	59	48.0%
3-4 pairs a year	16	13.0%
5-6 pairs a year	2	1.6%
7-8 pairs a year	1	0.8%
JeansPay (How much the person often pays for a pair of jeans)		
€0 – €10	5	4.1%
€10 – €20	14	11.4%
€20 – €30	37	30.1%
€30 – €40	18	14.6%
€40 – €50	20	16.3%
€50 – €60	5	4.1%
€60 – €70	8	6.5%
€70 – €80	4	3.3%
€80 – €90	2	1.6%
€80 – €100	6	4.9%
Over €100	4	3.3%

Regarding the spending habit, approximately two-thirds of the sample spend less than €40 on clothes every month. About 25% spend from €40 to €100, and less than 10% have a monthly expenditure of over €100 for clothes. In terms of jeans purchase frequency, 38% buy less than a pair per year. Nearly 50% of the respondents buy 1-2 pairs of jeans annually. Only 3 people buy more than 4 pairs, and nobody buys more than 8 pairs a year. With respect to the price usually paid for a pair of jeans, over 80% pay less than €60, which is similar to the price range in the choice experiment (€30 - €60).

4.3.3 Attitudinal profile

Table 8. Factor loadings of 15 attitudinal statements on 3 factors

Statements	ConcernEnv (Concern about environment)	ConcernSwt (Concern about Sweatshops)	Skepticism (Skepticism of eco-labels)
#1	0.912	.	.
#2	0.895	.	.
#3	0.728	.	.
#4	0.603	.	.
#5	0.647	.	.
#6	0.777	.	.
#7	.	0.659	.
#8	.	0.779	.
#9	.	0.863	.
#10	.	0.729	.
#11	.	0.744	.
#12R	.	.	0.488
#13	.	.	0.501
#14	.	.	0.824
#15	.	.	0.723
Cronbach's alpha	**0.878**	**0.872**	**0.713**

Attitudinal variables are measured in the survey by 15 statements on a 7-point scale (from Strongly disagree to Strongly agree). To check whether these 15 statements actually measure 3 separate constructs, an exploratory factor analysis (oblique rotation) was performed. Two types of rotations are possible: orthogonal or oblique. Orthogonal rotation assumes that the factors are not correlated, which is hardly the truth for psychological constructs. In contrast, oblique rotation allows correlations among factors, which is preferred in psychological research. Therefore, oblique rotation was used to analyze our 15 statements. The results confirmed our expectation: statements #1 to #6 fall under one factor, statements #7 to #11 constitute to the second factor, and the last 4 statements (with statement #12 being reverse coded) make up the third factor. Only loadings above 0.4 are shown in the above table. A reliability analysis was also conducted to check internal consistency of the three factors. All three Cronbach's alphas are above 0.7, which is the widely used threshold for reliability.

The score of each construct will be calculated by taking the average of its constituent items. First, the score for "ConcernEnv" is the average of items #1 to #6. "ConcernSwt" is the average of items #7 to #11. Finally, "Skepticism" is the average of items #12 (reverse coded), #13, #14 and #15.

The distribution of these three constructs in the sample is shown in the below table. It is clear that the distribution of "ConcernEnv" and "ConcernSwt" are skewed towards the high end. A large number of respondents chose 6 and 7 for their answers to items #1 - #11. Meanwhile, the distribution of "Skepticism" is more similar to a normal distribution, peaking at around 4.

Table 9. Sample characteristics (Attitudinal profile)

N = 123	Absolute	Relative (%)
ConcernEnv (Concern about the environment)		
From 1.00 to 2.00	1	0.8%
From 2.01 to 3.00	0	0.0%
From 3.01 to 4.00	0	0.0%
From 4.01 to 5.00	10	8.1%
From 5.01 to 6.00	30	24.4%
From 6.01 to 7.00	82	66.7%
ConcernSwt (Concerns about sweatshops)		
From 1.00 to 2.00	0	0.0%
From 2.01 to 3.00	2	1.6%
From 3.01 to 4.00	19	15.4%
From 4.01 to 5.00	25	20.3%
From 5.01 to 6.00	36	29.3%
From 6.01 to 7.00	41	33.3%
Skepticism (Skepticism of eco-label)		
From 1.00 to 2.00	0	0.0%
From 2.01 to 3.00	16	13.0%
From 3.01 to 4.00	40	32.5%
From 4.01 to 5.00	39	31.7%
From 5.01 to 6.00	20	16.3%
From 6.01 to 7.00	8	6.5%

A research by Abdul-Muhmin (2007) also reported a comparably high score for "Concern about the environment" when collecting responses from 232 people in Saudi Arabia. In that paper, the authors utilized more than 20 items to measure a variety of constructs, including 6 items used in this thesis project (#1 - #6). The means of these 6 items in that research was 5.97 when converted to a 7-point scale. For our sample, the mean of "ConcernEnv" is 6.29. Our slightly higher result may be due to the higher percentage of female in our sample (60%) than in Abdul-Muhmin's sample (34% female). The high education level and international composition of our sample can also contribute to the difference. Despite the small difference, both means are on the high end, suggesting that in general people are highly concerned about environmental issues. Meanwhile, the paper that measured "Concern about sweatshops" did not report the mean score for their sample (Phau et al., 2015), so no comparison is possible.

Regarding the "Skepticism of eco-labels", the mean of our sample is 4.28 on the 7-point scale. Hustvedt & Dickson (2011) reported a mean of 3.83 for their sample. Again, the small difference may be due to the sociodemographic characteristics of survey respondents. The sample of Hustvedt & Dickson consisted of only American consumers with nobody under 25 years old and nearly 80% over 44 years old, whereas our sample is much younger. Our sample is also more highly educated: 60% of respondents in our survey are studying or have completed a Master degree and above, compared to 25% in their sample. Nevertheless, both means are near the center value 4 on a 7-point scale, showing that people neither totally believe nor totally doubt the environmental claims on labels. These similarities demonstrate that our survey provides a comparable result to previous literature for the measurement of environmental concern and skepticism of eco-labels.

CHAPTER 5. DATA ANALYSIS

In order to analyze the collected data from the survey, we need to convert respondents' choices and their background variables into numbers. After that, a series of MultiNomial Logit (MNL) and Panel Mixed Logit (ML) discrete choice models can be estimated by Apollo package in RStudio (Hess & Palma, 2019). The R syntaxes are shown in Appendix F of this report. The systematic utility of the opt-out alternative was fixed at 0 (any other arbitrary values are also ok because only difference in utility matters). This chapter will illustrate the **Coding of choices** (5.1), then the **Coding of background variables** (5.2) and finally the **Model estimation** (5.3).

5.1 CODING OF CHOICES

Each choice set requires the respondents to answer two sub-questions:

(a) Which pair of jeans is preferred
(b) Whether the respondents will actually purchase the chosen pair of jeans from part (a)

Therefore, each set can be seen as a three-alternative set which includes:

- Alternative #1: Purchase the pair of jeans #1
- Alternative #2: Purchase the pair of jeans #2
- Alternative #3: Not purchase anything (opt-out option)

Based on respondents' answers to the two sub-questions, their choices will be coded as follows for the model estimation. A coding of "3" means that the respondent selects the opt-out alternative and does not purchase any pair of jeans.

Table 10. Distribution of respondents' choices

Answer to part (a)	Answer to part (b)	Coding	No. of observations	Percentage
Jeans #1	Yes	1	391	26.5%
Jeans #2	Yes	2	324	22.0%
Jeans #1	No	3	398	27.0%
Jeans #2	No	3	363	24.6%
		Total	1476	100.0%

The number and percentage of observations corresponding to each combination of answers are listed in the fourth and fifth columns respectively. There are 1476 observations in total (123 people with 12 choice sets each). The combinations of answers are quite evenly distributed with about 22%-27% for each combination. In more than half of the observations (51.6%), respondents selected the opt-out alternative. This strong preference for the opt-out option implies the presence of an alternative specific constant. In only 49.5% of the observations, the variations of attributes lead to a higher utility than this alternative specific constant, prompting people to purchase a pair of jeans. The results of model estimation which will be shown in a later section will confirm this expectation.

5.2 CODING OF BACKGROUND VARIABLES

The coding of all of background variables are presented in the below table. For continuous background variables that are divided into sub-categories (*Income, Clothes, JeansPay*), the midpoint of each category is used as the code, which allows interpretation of the estimated parameters in the variables' original units.

Table 11. Coding of background variables

Background variables name	Description	Coding
Gender	Female or Male	0 = Female 1 = Male
Age	Age on December 31st, 2020	19 – 63 (integers)
Education	Highest level of education	0 = Others 1 = High school 2 = Technical/Vocational training 3 = Bachelor degree 4 = Master degree 5 = PhD and above
Nationality	Country of nationality/citizenship	0 = Low- & Middle-income countries 1 = High-income countries
Residence	Country of residence	0 = Low- & Middle-income countries 1 = High-income countries
Income	Net annual income	5,000 = €0 – €10,000 15,000 = €10,000 – €20,000 25,000 = €20,000 – €30,000 ... 95,000 = €90,000 – €100,000 105,000* = over €100,000
Clothes	Monthly spending on clothes	10 = €0 - €20 30 = €20 - €40 50 = €40 - €60 ... 190 = €180 - €200 210* = over €200
JeansFreq	How often the respondent buys a pair of jeans	0 = less than a pair per year 1 = at least a pair per year
JeansPay	How much the respondent usually pays for a pair of jeans	5 = €0 - €10 15 = €10 - €20 25 = €20 - €30 ... 95 = €90 - €100 105* = over €100
ConcernEnv	Concern about the environment	Real number ranging from 1 (least concerned) to 7 (most concerned)
ConcernSwt	Concern about sweatshops	Real number ranging from 1 (least concerned) to 7 (most concerned)
Skepticism	Skepticism of eco-labels	Real number ranging from 1 (least skeptical) to 7 (most skeptical)

**Because the chosen categorical range cannot cover all respondents, an open-ended level is included with assumed equidistance in regard to the other categorical levels.*

For *JeansFreq*, the respondents are grouped into two broad categorical levels for model estimation:

- *Buying less than a pair of jeans per year*
  (including two original categories: a pair every 2-3 years, a pair every 4-5 years)
- *Buying at least a pair of jeans per year*
  (including four original categories: 1-2 pairs a year, 3-4 pairs a year, 5-6 pairs a year, 7-8 pairs a year)

There are two reasons for this coding choice. First, it ensures that the number of respondents for each level is large enough. Second, using six categorical levels requires estimating five separate parameters. Estimating fewer parameters is possible only if the variable is assumed to be continuous, which does not hold true for the original six categorial levels of *JeansFreq*. To maintain model parsimony, two levels are used instead of six.

The same rationale applies for *Nationality* and *Residence* variables. World Bank categorized countries into four different income groups based on their Gross National Income (GNI) per capita in current US dollars (latest data in 2018): Low income (< $1,026), Lower-middle income ($1,026 - $3,995), Upper-middle income ($3,995 - $12,375) and High income (> $12,375) (World Bank, 2020). To ensure a sufficient number of respondents for each level as well as to keep the model parsimonious, only two broader levels are used in the coding:

- *High income* (the same as World Bank's definition)
- *Low & middle income* (encompassing the remaining three categories: Low income, Lower-middle income, Upper-middle income).

Table 12. Number of respondents in each coded categorical level

Categorical levels	No. of respondents	Percentage
JeansFreq		
Less than a pair per year	45	36.6%
At least a pair per year	78	63.4%
Nationality		
High income	51	41.5%
Low & middle income	72	58.5%
Residence		
High income	104	84.6%
Low & middle income	19	15.4%

Combining the median values of all background variables, we can also construct the profile of a typical respondent, which is shown below. This hypothetical individual is relatively young (28 years old) and highly educated (studying or having a Master degree). She comes from a low & middle-income country, but currently lives in a high-income country. Her annual income is on the low end. In terms of spending habit, she spends quite little on clothes (only €20 - €40 per month - the second lowest category for this variable). She buys at least a pair of jeans per year for about €30 - €40, which is within the price range used in our stated choice experiment. Regarding her attitudinal profile, she is highly concerned about the environment and sweatshop issues, but quite neutral about the believability of eco-labels.

Table 13. Profile of a typical respondent

	Background variables	Median value	Description
Sociodemographic	Gender	0	Female
	Age	28	28
	Education	4	Master degree
	Nationality	0	Low & Middle income
	Residence	1	High income
	Annual net Income	15,000	€10,000 - €20,000
Spending habit	Monthly spending on clothes	30	€20 - €40
	Frequency of buying jeans	1	At least a pair per year
	Price usually paid for a pair of jeans	35	€30 - €40
Attitudinal	Concern about the environment*	6.67	6.67
	Concern about sweatshops*	5.40	5.40
	Skepticism about eco-labels*	4.25	4.25

**on the scale of 1-7 with 1 being least concerned/least skeptical and 7 being most concerned/most skeptical*

5.3 MODEL ESTIMATION

A total of 8 MNL models and 1 ML model were estimated. Their relationships are shown in the below diagram.

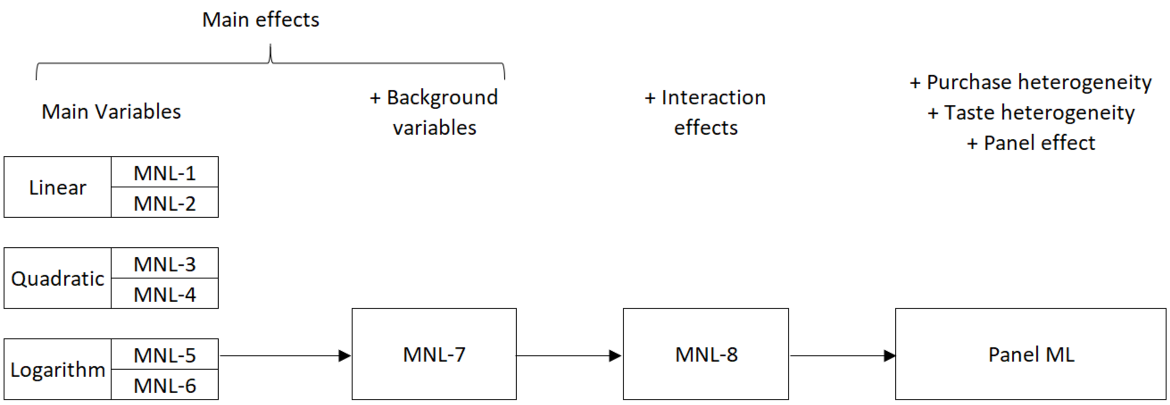


Figure 20. Relationship of estimated models

Starting with main effects of main variables, 6 MNL models (MNL-1 to MNL-6) were estimated. 3 different mathematical forms (linear, quadratic, logarithm) of ratings were compared. For each mathematical form, whether the respondents treat the two ratings (Env and Labor) separately or combine them into a single composite rating (EnvLabor) was tested. EnvLabor is equal to the sum of Env and Labor.

Then, the best-fitted model (MNL-5) was chosen to incorporate main affects of background variables (MNL-7). Next, interaction effects were added to MNL-7 to create MNL-8.

Finally, heterogeneities and panel effects were added to MNL-8 in order to generate the ML model.

5.3.1 MNL models (MNL-1 to MNL-8)

The following MNL models were tested:

- **Main effects of Main variables:**
  - MNL-1: linear form of environment (Env) and labor rights (Labor)
  - MNL-2: linear form of composite rating (EnvLabor)

  - MNL-3: linear + quadratic component of environment (Env^2) and labor rights ($Labor^2$)
  - MNL-4: linear + quadratic component of composite rating ($EnvLabor^2$)

  - MNL-5: logarithm form of environment (ln(Env)) and labor rights (ln(Labor))
  - MNL-6: logarithm form of composite rating (ln(EnvLabor))

- **Main effects of Background variables:**
  - MNL-7: background variables were added to MNL-5 (best-fitted among 6 models above)

- **Interaction effects:**
  - MNL-8: interaction effects was added to MNL-7

a) Main effects of Main variables (MNL-1 to MNL-6)

Linear (MNL-1 and MNL-2)

First, a simple MNL model with only main effects and linear form of all attributes was estimated (MNL-1). The systematic utility function was as follows:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{Env} \bullet Env_i + \beta_{Labor} \bullet Labor_i$$

$$V_{opt-out} = 0$$

Where V_i (i=1,2): systematic utility of buying the pair of jeans #1 or #2

$V_{opt-out}$: systematic utility of opt-out alternative (not buying), which is fixed at 0

ASC: alternative-specific constant, which is the base utility of buying a new pair of jeans compared to the out-out alternative

β_m: parameter of attribute m, which represents the weight (importance) of that attribute in influencing people's choices.

Price: price of the pair of jeans (30, 40, 50 or 60)

Origin: whether the pair of jeans is produced overseas (coding=0) or locally (coding=1)

Fiber: fiber content: 80% cotton + 20% others (coding=0) or 100% cotton (coding=1)

Wash: hand wash only (coding=0) or machine-washable (coding=1)

Dry: hang dry only (coding=0) or tumble dryable (coding=1)

Env: environment rating (1, 2, 3 or 4)

Labor: labor rating (1, 2, 3 or 4)

Estimation results of MNL-1 revealed that β_{Env} and β_{Labor} had comparably similar size. Therefore, a t-ratio test was conducted to check whether the difference between two parameters were statistically significant. The calculation was as follows:

$$t - ratio_{Env-Labor} = \frac{\beta_{Env} - \beta_{Labor}}{SE_{Env-Labor}}$$

with $SE_{Env-Labor} = \sqrt{VAR_{Env} + VAR_{Labor} - 2 \bullet COV_{Env,Labor}}$

Where $SE_{Env-Labor}$: standard error of the difference between β_{Env} and β_{Labor}

VAR_{Env}: variance of β_{Env}

VAR_{Labor}: variance of β_{Labor}
$COV_{Env,Labor}$: covariance of β_{Env} and β_{Labor}

The calculated t-ratio was 1.84, which was less than the threshold value of 1.96 at 5% significance level, so the difference between β_{Env} and β_{Labor} was not statistically significant. In other words, β_{Env} and β_{Labor} were not statistically different from each other. Therefore, it was wise to test whether people combined these two ratings instead of treating them separately, leading to model MNL-2.

A composite rating (EnvLabor), which was equal to the sum of environment rating and labor right rating, was incorporated to the model (MNL-2). Because environment rating and labor rights rating were integers ranging from 1 to 4, EnvLabor was also an integer but ranged from 2 to 8. The systematic utility function of MNL-2 was as follows:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{EnvLabor} \bullet EnvLabor_i$$

Where $EnvLabor_i = Env_i + Labor_i \qquad (EnvLabor_i \in \{1; 2; 3; \ldots; 8\})$

Quadratic (MNL-3 and MNL-4)

The previous two models MNL-1 and MNL-2 used only the linear form of environment (Env) and labor rights (Labor) ratings, which assumed that the utility contribution of these two attributes was linearly proportional to the respective ratings. In other words, marginal utility was assumed to be constant: the added utility when going from rating 1 to 2 is the same as when going from rating 2 to 3 as well as from rating 3 to 4. However, this is hardly the case in real life because improving the lowest rating 1 to rating 2 should be more important than improving a relatively higher rating 3 to rating 4.

According to the law of diminishing marginal utility in economics, marginal utility will decrease with increasing units of a good/service, implying that marginal utility curve should be convex around the origin, not a horizontal line. Total utility should be a concave curve which flattens out when the quantity (or rating in our case) increases more and more, not an upward straight line. Therefore, a quadratic component was added to the model to test whether the law of diminishing marginal utility held true in our case. The difference between linear and quadratic models is shown in the below figure.

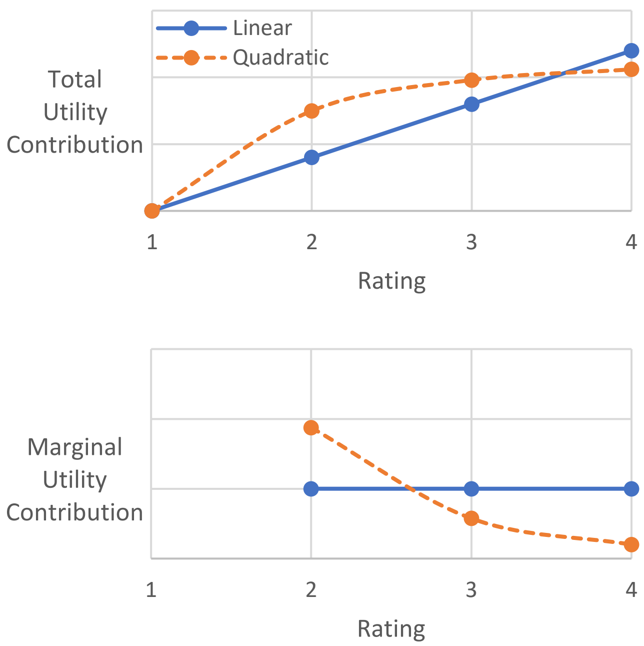


Figure 21. Total and marginal utility contribution of environment/labor rights rating

Quadratic components of environment (Env^2) and labor right ($Labor^2$) ratings were added to the systematic utility function of MNL-3:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{Env} \bullet Env_i + \beta_{Labor} \bullet Labor_i + \beta_{Env^2} \bullet Env_i^2 + \beta_{Labor^2} \bullet Labor_i^2$$

MNL-4 also included a quadratic component like MNL-3, but MNL-4 used the composite rating (EnvLabor) instead of two separate ratings for environment and labor rights. The systematic utility function was as follows:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{EnvLabor} \bullet EnvLabor_i + \beta_{EnvLabor^2} \bullet EnvLabor_i^2$$

Price is assumed to follow a linear form like in previous literature in the field of consumer research (Breidert et al., 2015; Kohli & Mahajan, 1991).

Logarithm (MNL-5 and MNL-6)

In MNL-3 and MNL-4, testing for deviation from linearity required an extra parameter for the quadratic component. To improve model parsimony, a logarithm form of the rating could be used instead. This approach had been demonstrated in a previous research by Molin et al. (2017). The shape of the logarithm curve was similar to that of the quadratic curve in the figure above. Logarithm form enabled us to estimate only 1 parameter instead of 2 parameters (1 linear component and 1 quadratic component) for each attribute, yet still maintained the property of diminishing marginal utility.

Therefore, natural logarithm form of environment and labor rights ratings were used in the systematic utility function of MNL-5:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{\ln(Env)} \bullet \ln(Env_i) + \beta_{\ln(Labor)} \bullet \ln(Labor_i)$$

MNL-6 was similar to MNL-5, but included the natural logarithm of the composite rating instead:

$$V_i = \text{ASC} + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i + \beta_{\ln(EnvLabor)} \bullet \ln(EnvLabor_i)$$

b) Main effects of Background variables (MNL-7)

MNL-5 had the best model fit among the above-mentioned 6 models. Consequently, MNL-5 was chosen to be tested for main effects of background variables (MNL-7).

Each background variable was tested individually for their main effect, which indicates the inclination to purchase the pair of jeans (compared to not purchasing). 7 out of 12 variables were significant. They were then added to the model at once. 3 variables were eliminated one by one by stepwise process (removing the parameter with the lowest t-ratio, then repeating the estimation). 4 variables remained significant at the end: Gender, Residence, Clothes and JeansFreq.

The systematic utility function is as follows (Blue is main effects of background variables):

$$\mathrm{V_i} = \text{ASC} + \beta_{\text{Price}} \bullet \text{Price}_\text{i} + \beta_{\text{Origin}} \bullet \text{Origin}_\text{i} + \beta_{\text{Fiber}} \bullet \text{Fiber}_\text{i} + \beta_{\text{Wash}} \bullet \text{Wash}_\text{i} + \beta_{\text{Dry}} \bullet \text{Dry}_\text{i} + \beta_{\ln(\text{Env})} \bullet \ln(\text{Env}_\text{i}) + \beta_{\ln(\text{Labor})} \bullet \ln(\text{Labor}_\text{i}) + \beta_{\text{Gender}} \bullet \text{Gender} + \beta_{\text{Residence}} \bullet \text{Residence} + \beta_{\text{Clothes}} \bullet \text{Clothes} + \beta_{\text{JeansFreq}} \bullet \text{JeansFreq}$$

c) Interactions (MNL-8)

Next, model MNL-7 was further improved by adding interaction effects. To maintain model parsimony, only interaction effects with Price, Env and Labor attributes were considered. Two types of interaction effects were estimated:

- First, interactions among the 3 main attributes (Price, Env, Labor) were tested: Price*ln(Env), Price*ln(Labor) and ln(Env)*ln(Labor). Both Price*ln(Env) and Price*ln(Labor) were not significant. Only ln(Env)*ln(Labor) was significant and was kept for the final model.
- Second, interactions of background variables (Gender, Age, Income, etc.) with Price, Env and Labor attributes were tested. There are 36 potential interactions in total (12 background variables multiplied by 3 main attributes). One interaction was tested at a time. 10 interactions were found to be statistically significant.

ln(Env)*ln(Labor) and all 10 significant interactions of background variables were added at once to the model, and the process of stepwise elimination (starting with the interaction having the lowest t-ratio) was repeated. At the end, only 7 remained significant.

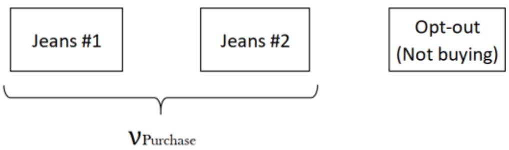
The systematic utility function of the final model (MNL-8) with those 7 interactions was as follows (Blue is main effects of background variables, Green is interaction effects):

$$
\begin{aligned}
V_i = {} & ASC + \beta_{Price} \bullet Price_i + \beta_{Origin} \bullet Origin_i + \beta_{Fiber} \bullet Fiber_i + \beta_{Wash} \bullet Wash_i + \beta_{Dry} \bullet Dry_i \\
& + \beta_{\ln(Env)} \bullet \ln(Env_i) + \beta_{\ln(Labor)} \bullet \ln(Labor_i) \\
& + \beta_{Gender} \bullet Gender + \beta_{Residence} \bullet Residence + \beta_{Clothes} \bullet Clothes + \beta_{JeansFreq} \bullet JeansFreq \\
& + \beta_{\ln(Env)*\ln(Labor)} \bullet \ln(Env_i) \bullet \ln(Labor_i) \\
& + \beta_{Price*Gender} \bullet Price_i \bullet Gender + \beta_{Price*Residence} \bullet Price_i \bullet Residence \\
& + \beta_{\ln(Env)*Gender} \bullet \ln(Env_i) \bullet Education + \beta_{\ln(Env)*Residence} \bullet \ln(Env_i) \bullet Residence \\
& + \beta_{\ln(Labor)*ConcernSwt} \bullet \ln(Labor_i) \bullet ConcernSwt + \beta_{\ln(Labor)*Skepticism} \bullet \ln(Labor_i) \bullet Skepticism
\end{aligned}
$$

5.3.2 PANEL ML MODEL

Next, panel ML models were built by incorporating the following properties, which were not possible with MNL models:

- **Purchasing heterogeneity** (compared to not purchasing):
  The alternative specific constant (ASC) indicates the tendency to purchase, which can be explained by other factors not varied in the experiment. In MNL models, ASC was assumed to be the same for all people. In ML model, ASC was allowed to follow a random distribution $\upsilon_{Purchase} \sim N(\mu_{Purchase}, \sigma_{Purchase})$, meaning that different people have different inclination to purchase:

  Adding the purchase heterogeneity $\upsilon_{Purchase}$ to the utility function accounts for the nesting effect (correlation between 2 purchase options: Jeans #1 and Jeans #2).
- **Taste heterogeneity** for Price, Env and Labor (only these 3 attributes were considered to avoid overcomplicating the model with too many parameters):
  Price is more important to some people than others, and so are Env and Labor. Therefore, the importance of each attribute should be different across different people. MNL models assumed

that all people attach the same importance to each of these 3 attributes when making their decisions, which is not realistic.

- **Panel effect** (correlation of choices made by the same individual):
  If one person cares more about Price in one choice set, he is likely to care more about it in other choice sets as well. Panel effect accounts for the stability of each individual regarding their taste across all their choices. In our case, 12 choices made by each person are assumed to follow a similar pattern. Without panel effect, all observations are treated as independent choices, and those 12 choices may have totally different patterns as if they were made by 12 different people.

Regarding the purchasing heterogeneity and taste heterogeneity, several random distributions for $\upsilon_{Purchase}$, β_{Price}, $\beta_{\ln(Env)}$ and $\beta_{\ln(Labor)}$ were evaluated. The model did not converge with LogNormal distributions of these parameters. Only Uniform and Normal distributions led to model convergence (after about 30-35 iterations). Normal distribution gave better model fit (higher log-likelihood and Rho-square) than Uniform distribution. The final model with normally distributed parameters will be shown in the results section.

First, 250 Halton draws from the normal distributions were used. Then the number of draws was doubled to 500, which did not generate any significant differences from 250 draws. Therefore, 250 draws were concluded to be sufficient for the models.

Heterogeneity for Purchase, Env and Labor were significant, so they were kept as randomly distributed parameters. In contrast, the Price parameter was not significant, so it was evaluated as a crisp value.

Some background variables and interaction effects also become insignificant, so the process of stepwise elimination (starting with the parameter having the lowest t-ratio) was repeated until only significant background variables and interactions remained. In the final model, only 1 background variable and 4 interactions were kept in the model.

The systematic utility is as follows (Blue is main effect of background variable, Green is interactions):

$$
\begin{aligned}
V_i = {} & \upsilon_{\text{Purchase}} + \beta_{\text{Price}} \bullet \text{Price}_i + \beta_{\text{Origin}} \bullet \text{Origin}_i + \beta_{\text{Fiber}} \bullet \text{Fiber}_i + \beta_{\text{Wash}} \bullet \text{Wash}_i + \beta_{\text{Dry}} \bullet \text{Dry}_i \\
& + \beta_{\ln(\text{Env})} \bullet \ln(\text{Env}_i) + \beta_{\ln(\text{Labor})} \bullet \ln(\text{Labor}_i) \\
& + \beta_{\text{JeansFreq}} \bullet \text{JeansFreq} \\
& + \beta_{\text{Price}*\text{Gender}} \bullet \text{Price}_i \bullet \text{Gender} \\
& + \beta_{\text{Price}*\text{Residence}} \bullet \text{Price}_i \bullet \text{Residence} \\
& + \beta_{\ln(\text{Labor})*\text{ConcernSwt}} \bullet \ln(\text{Labor}_i) \bullet \text{ConcernSwt} \\
& + \beta_{\ln(\text{Labor})*\text{Skepticism}} \bullet \ln(\text{Labor}_i) \bullet \text{Skepticism}
\end{aligned}
$$

where

$$
\begin{aligned}
& \upsilon_{\text{Purchase}} \sim N(\mu_{\text{Purchase}}, \sigma_{\text{Purchase}}); \\
& \beta_{\ln(\text{Env})} \sim N\left(\mu_{\ln(\text{Env})}, \sigma_{\ln(\text{Env})}\right); \\
& \beta_{\ln(\text{Labor})} \sim N\left(\mu_{\ln(\text{Labor})}, \sigma_{\ln(\text{Labor})}\right)
\end{aligned}
$$

5.5 MODEL FIT COMPARISON

A model that fits the dataset better will result in more accurate calculations of willingness to pay and choice probability. Therefore, it is important to compare the model fit among our estimated models (MNL-1 to MNL-8 and panel ML models). How well a model fits the dataset can be measured by the log-likelihood and McFadden's Rho-square, which will be discussed in this part.

5.5.1 Log-likelihood

Estimation result of a model gives the log-likelihood of that model. The higher the log-likelihood (the closer it is to 0), the better the model fit. However, when we use more parameters, log-likelihood may increase due to capturing more peculiarities of the sample. We cannot say for sure if the new model (with more parameters) is actually better. If the original model A can be nested in the new model B (by restricting values of some parameters), we use the likelihood ratio statistics (LRS) to compare log-likelihood of models A and B:

$LRS = -2 * (LL_{\text{Model A}} - LL_{\text{Model B}})$

The null-hypothesis is that A is the true data generation process in the population. We try to see what is the probability of B giving better results (higher log-likelihood) due to chance. By comparing LRS with threshold values in Chi-square table at the degree of freedom q (number of extra parameters in B compared to A), we can estimate that probability. For example, if LRS > threshold value at 5%, we can say that there is only 5% chance of B being better than A due to randomness. In other words, B is better than A at 5% significance level.

5.5.2 Adjusted McFadden's Rho-square

McFadden's Rho-square: $\rho^2 = 1 - \frac{LL(final)}{LL(0)}$

where *LL(final)* is the log-likelihood of estimated model
LL(0) is the log-likelihood of initial model (when all betas are 0)

McFadden's Rho-square provides the percentage of uncertainty explained by the model. The higher the value, the better the model explains the variation of the dataset. Rho-square ranges from 0 to 1:

- $\rho^2 = 0$: the model is as good as throwing a dice/coin
- $\rho^2 = 1\ (impossible)$: perfect fit, the model explains all choices with 100% certainty

When the number of parameters increases, Rho-square often becomes higher. Therefore, to compare models with different number of parameters, a modified formula was used to calculate the adjusted Rho-square:

$\text{Adjusted } \rho^2 = 1 - \frac{\text{LL(final)} - \text{K}}{\text{LL(0)}}$ where K is the number of parameters in the model.

CHAPTER 6. RESULTS

The estimation results are presented in this section. All reported t-ratios are robust values, and the Rho-squares are the adjusted values which take the number of parameters into account.

6.1 MNL MODELS

6.1.1 Main effects of Main variables (MNL-1 to MNL-6)

As can be seen from the results table of MNL models, the constant (ASC) and estimated parameters of Price, Fiber and Wash are statistically significant with robust t-ratios larger than 1.96 (the threshold value at 5% significance level), whereas the parameter of Dry attribute is not significant in all models. The parameter of Origin attribute is only significant in model MNL-6, and not significant in all other models. The t-ratio of β_{Origin} is higher than that of β_{Dry} in all cases, so the Origin attribute may reach statistical significance before the Dry attribute when we increase the sample size. However, based on our current sample size, the influence of manufacturing country (Origin) and the use of tumble dryer (Dry) on people's choices is not statistically significant.

This result may stem from the diversity of respondents in the survey. Some people want to support local businesses by buying from local brands, whereas others prefer imported clothes due to their perceived higher quality, more fashionable style and better brand image. A research of Dickson et al. (2004) showed that some Chinese consumers favor locally made clothes while others prefer foreign-made apparel. Regarding the Dry attribute, weather and culture may influence people's choices. Some countries with cold and rainy climate may prefer to use tumble dryer, whereas tropical countries have no issues with hang drying. These wide-ranging differences in preference for manufacturing country and drying method might have resulted in high standard errors of the Origin and Dry parameters.

Next, all significant parameters have the expected signs. ASC is negative, revealing the base preference for the opt-out alternative. Many other factors not included in the experiment can affect consumers' preference, which is captured in ASC. ASC is the utility value of an alternative compared to base when all attributes have contribution 0. It represents the average inclination to purchase. Because ASC in this case is negative, people prefer not to buy if only factors not included in the experiment are taken into account. Only when the combination of attribute levels in a particular alternative produces a higher utility than the absolute value of ASC (hence leading to a positive V_i), the individual will make the purchase. Otherwise, V_i will be negative, which is lower than $V_{opt\text{-}out}$ (fixed at 0), and the opt-out alternative will be the preferred choice. From the collected observations, the opt-out alternative was chosen in about 50% of all choice sets. Price also has a negative parameter, which is expected for consumer goods. The higher the price, the lower the utility.

In contrast, the parameters for Fiber and Wash are positive. People participating in the survey prefer pure cotton (coding=1) compared to mixed fiber (coding=0). Some participants might understand the benefit of pure cotton jeans (more comfort and higher breathability), whereas others might just chose the pure cotton option due to a general favorable view of this fiber type. As expected, using washing machine (coding=1) is more favorable than hand washing (coding=0). It is especially important for the case of jeans which is made of thick fabric and thus difficult to be washed by hands.

Table 14. Estimation results of MNL-1 to MNL-6 models

Attributes	LINEAR				QUADRATIC				LOGARITHM			
	MNL-1		MNL-2		MNL-3		MNL-4		MNL-5		MNL-6	
	Estimate	t-Ratio	Estimate	t-Ratio	Estimate	t-Ratio	Estimate	t-Ratio	Estimate	t-Ratio	Estimate	t-Ratio
ASC	-3.353	-10.911	-3.308	-10.760	-4.653	-8.959	-2.600	-3.641	-2.586	-9.112	-5.078	-11.735
Price	-0.030	-6.722	-0.031	-6.833	-0.033	-6.857	-0.032	-6.878	-0.032	-7.178	-0.029	-6.459
Origin	0.128	1.402	0.132	1.464	0.132	1.392	0.100	1.053	0.133	1.482	0.203	2.216
Fiber	0.446	5.045	0.443	4.985	0.415	4.709	0.459	5.098	0.426	4.862	0.403	4.633
Wash	0.861	8.981	0.845	8.914	0.945	9.187	0.822	8.441	0.950	9.606	0.882	9.234
Dry	-0.091	-0.966	-0.084	-0.891	-0.036	-0.372	-0.077	-0.814	-0.044	-0.458	-0.111	-1.199
Env	0.645	14.086			1.335	4.473						
Labor	0.542	12.973			1.075	3.811						
EnvLabor*			0.590	16.853			0.335	1.435				
Env^2					-0.133	-2.392						
Labor^2					-0.097	-1.825						
EnvLabor^2							0.023	1.103				
ln(Env)									1.455	13.419		
ln(Labor)									1.310	12.687		
ln(EnvLabor)											2.949	14.965
Initial-LL	-1621.552											
Final-LL	-1282.609		-1284.296		-1277.237		-1283.715		-1277.403		-1291.684	
Adj. Rho square	0.2041		0.2037		0.2062		0.2034		0.2073		0.1991	
Parameters	8		7		10		8		8		7	

EnvLabor = Env + Labor (composite rating)

Underlined: *Not significant at 5%*

The results for environment and labor rights ratings are different across the categories (linear, quadratic, logarithm), which will be discussed separately in the following sections.

Linear (MNL-1 and MNL-2)

In MNL-1, Env and Labor attributes have positive parameters as expected. Higher environment and labor rights ratings generate higher utility. This result is consistent with the belief that consumers prefer fashion products manufactured in an environmentally friendly and ethical way. The respondents in our survey attached a significant importance to environment and labor rights ratings when making their purchase decisions.

In MNL-2, the parameter for composite rating EnvLabor is also positive as expected and also highly significant (t-ratio is nearly 18). Again, this result confirmed that higher ratings lead to higher utility for consumers. The value of $\beta_{EnvLabor}$ in MNL-2 is between the values of β_{Env} and β_{Labor} in MNL-1. The utility contribution range, which is the difference between the highest and lowest utility contribution, of EnvLabor is roughly equal to the sum of that of Env and Labor. Because the parameter size of other attributes (Price, Origin, Fiber, Wash, Dry) are similar in both models, their respective relative importance will be approximately the same. Meanwhile, the relative importance of EnvLabor will be the sum of that of Env and Labor.

Table 15. Utility contribution range of Env and Labor (in MNL-1) and EnvLabor (MNL-2)

	Estimated parameter	Rating values		Utility contribution		Utility contribution range
		Lowest	Highest	Lowest	Highest	
Env (MNL-1)	0.645	1	4	0.645	2.580	**1.935**
Labor (MNL-1)	0.542	1	4	0.542	2.168	**1.626**
EnvLabor (MNL-2)	0.590	2	8	1.180	4.720	**3.540**

Comparing the model fit, both models have similar adjusted Rho-square (0.2041 for MNL-1 and 0.2037 for MNL-2). These values of adjusted Rho-square are in the range of a good model fit, which is from 0.2 to 0.4 (McFadden, 1977). Regarding the log-likelihood, MNL-1 has an improvement of 1.687, corresponding to a likelihood ratio statistics (LRS) of 3.374. With 1 degree of freedom (MNL-1 has 1 more parameter than MNL-2), this LRS corresponds to a p-value between 10% and 5% in the Chi-square table. Therefore, MNL-1 cannot be confirmed to perform better than MNL-2 at 5% significance level. We cannot say which model is statistically better, so we do not know with certainty whether people treat the ratings separately or combine them into a single score. As a result, both cases (separate ratings and composite rating) were tested for non-linearity in the next step.

Quadratic (MNL-3 and MNL-4)

In MNL-3, quadratic component of environment rating is significant but that of labor right rating is not. It is either because the labor right rating actually has only linear contribution to the utility or because the number of observations is not large enough for the parameter β_{Labor^2} to reach statistical significance. In MNL-4, both linear and quadratic components of the composite rating EnvLabor is not significant, meaning that people do not care about the ratings if MNL-4 is the true data generation process. This is contradicting to all other models where the ratings of environment and labor rights influence people's choices.

Comparing the model fit, MNL-3 has higher adjusted Rho-square and LRS of 12.956, which is larger than 9.21 (the threshold at 1% and 2 degree of freedom). Therefore, the model fit of MNL-3 is statistically better than that of MNL-4 even at 1% significance level. In brief, when quadratic component was added, the model with separate ratings could explain the dataset better than the model with a composite rating.

Logarithm (MNL-5 and MNL-6)

When logarithm form is used instead of quadratic form, parameters for both separate ratings (MNL-5) and composite rating (MNL-6) are statistically significant. Similar to the case of linear models, utility contribution range of the composite rating is compared against that of separate ratings. Again, the utility contribution range of the composite rating EnvLabor is equal to the sum of that of Env and Labor.

Table 16. Utility contribution range of Env and Labor (in MNL-5) and EnvLabor (MNL-6)

	Estimated parameter	Rating values		Utility contribution		Utility contribution range
		Lowest	Highest	Lowest	Highest	
ln(Env) (MNL-5)	1.455	ln(1)	ln(4)	0	2.017	**2.017**
ln(Labor) (MNL-5)	1.310	ln(1)	ln(4)	0	1.816	**1.816**
ln(EnvLabor) (MNL-6)	2.949	ln(2)	ln(8)	2.044	6.132	**4.088**

The model with separate ratings (MNL-5) fit the dataset better than the model with composite rating (MNL-6). MNL-5 has higher adjusted Rho-square. Besides, log-likelihood of MNL-5 is about 14 points higher than MNL-6 even though MNL-5 has only 1 extra parameter. LRS is 28.562, which is larger than the threshold of 6.63 at 1% significance level and 1 degree of freedom. In both quadratic and logarithm forms, the models with separate ratings explain the variation of our dataset better than the models with composite ratings, as proven by LRS and Rho-square. To conclude, when the law of diminishing marginal utility is considered in the model, the dataset is more likely when the ratings are treated separately instead of being combined into a composite score.

6.1.2 Main effects of Background variables (MNL-7)

Among the above-mentioned 6 models, MNL-3 (quadratic form of separate ratings) and MNL-5 (logarithm form of separate ratings) have the highest log-likelihood. Both are consistent with the law of diminishing marginal utility. However, the logarithm form uses 2 fewer parameters. Therefore, MNL-5 is statistically better and chosen for testing the influence of background variables.

Out of 12 background variables, 7 were found to be significant when added separately to the model. Main effects of background variables indicate a stronger inclination to purchase.

Table 17. Effects of background variables on inclination to purchase
(Blue: significant; Grey: not significant)

Background variables	Significance	Explanation
Gender	+	Men are MORE inclined to purchase than women
Age		Does not influence the inclination to purchase
Education		Does not influence the inclination to purchase
Nationality		Does not influence the inclination to purchase
Residence	-	Residents in high-income countries are LESS inclined to purchase than residents in low- & middle-income countries
Income		Does not influence the inclination to purchase
Clothes	+	People spending more on clothes per month are MORE inclined to purchase

JeansFreq	+	People buying jeans more frequently are MORE inclined to purchase
JeansPay	+	People paying more for each pair of jeans are MORE inclined to purchase
ConcernEnv	-	People who are more concerned about the environment are LESS inclined to purchase
ConcernSwt	-	People who are more concerned about sweatshops are LESS inclined to purchase
Skepticism		Does not influence the inclination to purchase

(+ or - indicates the sign of the parameter)

When the above 7 significant background variables were added together at once to the model, 4 of them remain significant: Gender, Residence, Clothes, JeansFreq. That means the effects of these 4 variables are stronger than the other 3 variables. The estimation results of the model with these 4 variables are shown below. This is model MNL-7

Table 18. Estimation results of MNL-7

	Attributes	Estimate	Robust t-ratio
Main	ASC	-3.156	-9.479
	Price	-0.033	-7.255
	Origin	0.152	1.667
	Fiber	0.430	4.811
	Wash	0.980	9.698
	Dry	-0.055	-0.564
	ln(Env)	1.507	13.542
	ln(Labor)	1.346	12.997
Background	Gender	0.380	3.118
	Residence	-0.465	-2.654
	Clothes	0.009	4.886
	JeansFreq	0.580	4.316
Model Fit	Initial-LL	-1621.552	
	Final-LL	-1226.004	
	Adj. Rho-square	0.2365	
	Parameters	12	

Underlined: *Not significant at 5%*

Comparing the model fit of MNL-7 with MNL-5, the adjusted Rho-square improves from 0.2073 to 0.2365, or about 3% more of variations in the dataset can be explained when adding background variables. The log-likelihood also rises remarkably from -1277.403 for MNL-5 to -1226.004 for MNL-7, giving a LRS of 102.798. This LRS is much larger than the threshold of 13.28 at 1% significance level (4 degree of freedom). Therefore, there is almost 0% probability that the better model fit of MNL-7 is due to chance.

6.1.3 Interactions (MNL-8)

Only interactions of Price, Env and Labor were considered to maintain model parsimony. Origin, Fiber, Wash and Dry were assumed to not interact with other variables.

a) Out of the 3 interactions among main attributes (Price*ln(Env), Price*ln(Labor) and ln(Env)*ln(Labor)), only Env and Labor interact significantly with each other. The interaction parameter of Env with Labor is positive, meaning that higher environment rating increases the importance of labor rights rating and vice versa.
b) When each interaction of a background variable with a main attribute was tested, 10 out of 36 interactions were significant. The result is shown in the below matrix.

Table 19. Interaction effects between background and main variables (Blue: significant; Grey: not significant)

	Price	ln(Env)	ln(Labor)
Gender	+		
Age			
Education		+	
Nationality			+
Residence	-	-	
Income			
Clothes			
JeansFreq			
JeansPay	+		
ConcernEnv			
ConcernSwt			+
Skepticism	-	-	-

(+ or - indicates the sign of the parameter)

It can be seen from the above table that 5 background variables (Age, Income, Clothes, JeansFreq, ConcernEnv) do not interact significantly with any of the 3 main variables. Therefore, these background variables do not influence the importance of Price, Env and Labor.

The other 7 background variables (Gender, Education, Nationality, Residence, JeansPay, ConcernSwt and Skepticism) have at least 1 significant interaction. Men are less affected by price. People with higher education levels attach higher importance to environment rating. Citizens of high-income countries care more about labor rights rating than those coming from low- and middle-income countries. In contrast, residents living in high-income countries care less about the environment rating. They are also more sensitive to price change. People who usually pay more for a pair of jeans are less affected by price. People who are more concerned about sweatshops care more about labor rights rating. People who are more skeptical of eco-labels care more about price, but care less about environment and labor rights rating. None of these interactions were unreasonable.

It is important to note that the above interactions were significantly when they were added to the model one by one (the model had only 1 interaction at a time). When all significant interactions were added together at once to the model, some become insignificant (the dataset is not large enough to make all of them significant simultaneously). By stepwise elimination starting with the lowest t-ratio, 4 interactions were removed, and 7 interactions remained significant in the model MNL-8.

Table 20. Estimation results of MNL-8

	Attributes	Estimate	Robust t-ratio
Main	ASC	-3.538	-5.004
	Price	<u>-0.023</u>	<u>-1.953</u>
	Origin	<u>0.105</u>	<u>1.104</u>
	Fiber	0.459	5.046
	Wash	1.015	9.957
	Dry	<u>-0.001</u>	<u>-0.008</u>
	ln(Env)	<u>0.817</u>	<u>1.816</u>
	ln(Labor)	<u>0.759</u>	<u>1.872</u>
Background	Gender	-0.948	-2.316
	Residence	1.559	2.308
	Clothes	0.009	4.765
	JeansFreq	0.695	5.023
Interactions	Env*Labor	0.781	2.909
	Price*Gender	0.032	3.562
	Price*Residence	-0.034	-2.631
	ln(Env)*Education	0.145	2.368
	ln(Env)*Residence	-0.745	-2.417
	ln(Labor)*ConcernSwt	0.114	2.342
	ln(Labor)*Skepticism	-0.164	-3.378
Model Fit	Initial-LL	-1621.552	
	Final-LL	-1199.295	
	Adj. Rho-square	0.2487	
	Parameters	19	

<u>Underlined:</u> *Not significant at 5%*

Adding several interactions to the model make the main parameters of Price, Env and Labor become slightly insignificant (their t-ratios are slightly below 1.96), indicating that the interactions play a stronger role than the main effects in explaining the influence of these attributes on people's decisions.

Comparing the model fit of MNL-8 with MNL-7, the adjusted Rho-square improves from 0.2365 to 0.2487, or over 1% more of variations in the dataset can be explained when adding interaction effects. The log-likelihood also rises from -1226.004 for MNL-7 to -1199.295 for MNL-8, giving a LRS of 53.418. This LRS is much larger than the threshold of 18.48 at 1% significance level (7 degree of freedom). MNL-8 is statistically better than MNL-7 at 1% significance level. To sum up, MNL-8 provides the best model fit among all MNL models.

6.2 PANEL ML MODEL

To further improve the model fit, purchase heterogeneity, taste heterogeneity and panel effect were incorporated to model MNL-8, leading to panel ML model. Some main effects of background variables and some interactions became insignificant, so they were removed sequentially by stepwise elimination until only significant background variables and interactions remained. At the end, 1 background variable (JeansFreq) and 4 interactions were kept in the final model.

Price parameter was evaluated as a crisp value (its sigma is not significant and thus removed from the final model), meaning that Price is assumed to have the same level of importance for all respondents. In contrast, the sigma of Purchase, Env and Labor are significant, meaning that there is indeed difference among people regarding their inclination to purchase, the importance of environment rating and the importance of labor rights rating. This variation of Purchase (inclination to buy versus opting-out) is due to factors other than the main attributes and background variables in the survey. Normal distribution ensures model convergence and better model fit, so the parameter of Purchase, Env and Labor are assumed to be normally distributed. The mean and sigma of the normal distributions are reported in the below table.

Table 21. Estimation results of panel ML model

	Attributes	Estimate	Robust t-ratio
Main	Purchase	-5.302	-6.400
	Price	-0.034	-2.578
	Origin	<u>0.221</u>	<u>1.916</u>
	Fiber	0.492	4.231
	Wash	1.311	8.856
	Dry	<u>0.074</u>	<u>0.686</u>
	ln(Env)	2.486	10.016
	ln(Labor)	<u>1.138</u>	<u>1.614</u>
Background	JeansFreq	1.705	3.165
Interactions	Price*Gender	0.026	2.688
	Price*Residence	-0.035	-2.767
	ln(Labor)*ConcernSwt	0.495	5.047
	ln(Labor)*Skepticism	-0.328	-3.182
Heterogeneity	sigma Purchase	4.331	7.863
	sigma ln(Env)	-0.845	-3.336
	sigma ln(Labor)	-0.777	-3.038
Model Fit	Initial-LL	-1621.552	
	Final-LL	-943.8916	
	Adj. Rho-square	0.4080	
	Parameters	16	

<u>Underlined:</u> *Not significant at 5%*

Regarding the significance of main parameters, Origin, Dry and Labor are not significant, whereas the rest are significant. The manufacturing country and drying instructions probably did not influence respondents' choices. Labor is not significant because it is also involved in two interactions. These two interactions are stronger than the main effects of Labor in influencing people's choices.

With respect to the signs of the main parameters, all are consistent with expectation. The Purchase parameter is negative, showing that there was a base preference for not buying. Price also has a negative parameter: lower price leads to higher utility, and is preferred over higher price. Both parameters of Fiber and Wash have positive sign, meaning that people prefer pure cotton jeans and machine-washable clothes. Env and Labor also have positive parameter, demonstrating the preference for higher rating. Higher environment and labor rights ratings generate higher utility for consumers.

In terms of background variables, only the main effect of JeansFreq remained significant at the end. The positive sign of JeansFreq parameter demonstrates that people who buy jeans more frequently are less likely to opt out.

With respect to interactions, Price has 2 significant interactions with Gender and Residence, while Labor has 2 significant interactions with ConcernSwt and Skepticism. None of the interactions with Env are significant in the final model. The parameter of Price*Gender is positive, meaning that men are less affected by price than women when making their choices. Price*Residence has a negative parameter, showing that residents in high-income countries attach more importance to price. Labor has positive interaction parameter with ConcernSwt and negative interaction parameter with Skepticism. Therefore, people who are more concerned about sweatshops are also more concern about labor rights rating. Conversely, people who are more skeptical of eco-labels care less about the labor rating.

Taking all interactions into account, the full parameter of Price ($\beta_{Price} + \beta_{Price*Gender} \bullet Gender + \beta_{Price*Residence} \bullet Residence$) is negative for all combinations of Gender and Residence (men or women living in high-income or low- & middle-income countries). It can be said that lower price is preferred by all sub-groups of the sample. Meanwhile, the full parameter of Labor ($\beta_{\ln(Labor)} + \beta_{\ln(Labor)*ConcernSwt} \bullet ConcernSwt + \beta_{\ln(Labor)*Skepticism} \bullet Skepticism$) is positive on the full range of ConcernSwt and Skepticism. In our sample, the ConcernSwt value ranges from 2.40 to 7.00, whereas the Skepticism value ranges from 2.25 to 7.00 (which is shown in Appendix E). Therefore, higher labor rights rating is preferred by all people in our sample.

Comparing with the best MNL model (MNL-8), panel ML models fit the dataset remarkably better. Adjusted Rho-square improves considerably from about 0.25 for MNL-8 to 0.41 for panel ML models. This result means that about 41% of variation in the dataset can be explained by the estimated panel ML models. The final panel ML model used only 16 parameters instead of 19 parameters in MNL-8. Despite using fewer parameters, panel ML model still has much higher log-likelihood (about -950) compared to MNL-8 (about -1200). In brief, panel ML model is much more likely to be the true data generation process in the population than MNL models.

In the next sections, estimation results of panel ML model will be used to evaluate the relative importance of attributes, willingness to pay and choice probabilities.

6.3 RELATIVE IMPORTANCE

Relative importance of an attribute is calculated as follows (Halbrendt et al., 1995).

$$RI_i = 100 \cdot \frac{UR_i}{\sum_{j=1}^{n} UR_j}$$

where *RI_i* is the relative importance of attribute i
UR_i is the utility range of attribute i (the difference between the highest and the lowest utility contribution)

In the below table, the parameters of Price and Labor are calculated for a "typical" respondent with the median values of interacting background variables (Gender = 0, Residence = 1, ConcernSwt = 5.40, Skepticism = 4.25). Therefore, the corresponding relative importance is for an individual who are women, living in high-income country, scoring 5.40 on the ConcernSwt scale and 4.25 on the Skepticism scale. This particular individual is quite concerned about sweatshops and neutral in terms of skepticism.

Table 22. Relative importance of attributes

Attributes	Estimated parameter	Rating values		Utility contribution		Utility range	Relative Importance
		Lowest	Highest	Lowest	Highest		
Price	-0.069	60	30	-4.160	-2.080	2.080	19.0%
Origin	0.221	0	1	0.000	0.221	0.221	2.0%
Fiber	0.492	0	1	0.000	0.492	0.492	4.5%
Wash	1.311	0	1	0.000	1.311	1.311	11.9%
Dry	0.074	0	1	-0.074	0.000	0.074	0.7%
Env	2.486	ln(1)	ln(4)	0.000	3.447	3.447	31.4%
Labor	2.416	ln(1)	ln(4)	0.000	3.350	3.350	30.5%

The above table reveals that Price, Environment rating and Labor rating play the most important role in respondents' answers to the choice tasks. Together, these three attributes account for about 80% of the utility. The remaining four attributes (Wash, Fiber, Origin and Dry) account for only 20% of the utility. Environment and labor rights rating are the most important with about 31% each, followed by Price with 19%. Wash is in fourth place with about 12%. Fiber contributes less than half of what Wash contributes to the total utility. Origin is the second least important with only about 2%. Finally, Dry attribute makes almost no contribution to utility.

6.4 WILLINGNESS TO PAY

Willingness to Pay (WtP) is defined as the ratio of the partial derivative of systematic utility with respect to the studied attribute and to price. Because the parameter of price is negative, a minus sign in front of the formula is required, giving positive values of willingness to pay. Consumers prefer higher rating (positive rating parameter) and lower price (negative price parameter). To keep the utility constant, an increase in price (negative utility contribution) is required to compensate for an increase in ratings (positive utility contribution).

Using panel ML model, the willingness to pay for improving 1 point of Environment and Labor rights rating are:

$$\mathrm{WtP_{Env}} = -\frac{\frac{\partial V}{\partial \mathrm{Env}}}{\frac{\partial V}{\partial \mathrm{Price}}} = -\frac{\beta_{\ln(\mathrm{Env})}/\mathrm{Env}}{\beta_{\mathrm{Price}} + \beta_{\mathrm{Price*Gender}} \bullet \mathrm{Gender} + \beta_{\mathrm{Price*Residencce}} \bullet \mathrm{Residence}}$$

$$\mathrm{WtP_{Labor}} = -\frac{\frac{\partial V}{\partial \mathrm{Env}}}{\frac{\partial V}{\partial \mathrm{Price}}} = -\frac{[\beta_{\ln(\mathrm{Labor})} + \beta_{\ln(\mathrm{Labor})*\mathrm{ConcernSwt}} \bullet \mathrm{ConcernSwt} + \beta_{\ln(\mathrm{Labor})*\mathrm{Skepticism}} \bullet \mathrm{Skepticism}]/\mathrm{Labor}}{\beta_{\mathrm{Price}} + \beta_{\mathrm{Price*Gender}} \bullet \mathrm{Gender} + \beta_{\mathrm{Price*Residencce}} \bullet \mathrm{Residence}}$$

The willingness to pay of each rating is inversely proportional to its initial value because Environment and Labor ratings are in logarithm form. It also depends on the background variables with which the rating interacts. In this section, the willingness to pay for a "typical" consumer with median values of all background variables will be reported.

In our panel ML model, the parameters of Env and Labor follow normal distributions. Therefore, willingness to pay can only be estimated by the method of simulation. Based on the mean and the standard deviation of the distribution, 10,000 random draws from the normal distribution of β_{Env}, and 10,000 random draws from the normal distribution of β_{Labor} were taken (10000 was tested and shown to be a sufficient number, providing stable values for WtP). β_{Price} was a crisp value, so no draws were necessary. For each pair of draws, willingness to pay will be calculated. Then we can obtain the median of the 10,000 values of willingness to pay. The below table shows the willingness to pay calculated with median values of background variables.

Table 23. WtP (in euro's) of a typical respondent with median background variables (Female, Living in high-income country, ConcernSwt = 5.40 and Skepticism =4.25)

a) WtP for improving environment rating

Env rating	*10th-percentile*	*Mean/Median*	*90th-percentile*
1→2	21	36	51
2→3	10	18	25
3→4	7	12	17

a) WtP for improving labor rights rating

Labor rating	*10th-percentile*	*Mean/Median*	*90th-percentile*
1→2	20	35	49
2→3	10	17	25
3→4	7	12	16

The calculated willingness to pay are normally distributed, so the mean and the median are the same.

First, all results of willingness to pay are positive (significantly different from 0), meaning that people are willing to pay more money for the improvement in Environment and Labor rights ratings. The mean value of willingness to pay ranges from €12 to €36 for each rating. From a business perspective, when a company improves each rating by one unit, they can charge €12 to €36 more per product item without losing the market share.

When we compare 3 rows of each table, it is obvious that when the initial rating increases, the willingness to pay decreases. For example, the mean willingness to pay for Environment rating is €36 euro for initial rating 1, but only €18 for initial rating 2, and decreasing to €12 for initial rating 3. In all tables, the willingness to pay for the improvement 2→3 and 3→4 is approximately half and one-third of that for the improvement 1→2 respectively. This trend is consistent with the expected diminishing marginal utility of the logarithm function. Marginal utility goes down when the rating increases, so the improvement in rating becomes less important when the initial rating is higher. In other words, when the fashion company performs very poorly in terms of environment or labor rights issues (eg. rating of 1), consumers are willing to pay a comparably high amount to improve their performance. In contrast, when the company has a relatively good performance (eg. rating of 3), consumers are only willing to pay a smaller amount for further improvement.

6.5 CHOICE PROBABILITY AND APPLICATION

In MNL model, choice probability of alternative i can be calculated from the formula: $P(i) = \frac{e^{V_i}}{\sum_{j=1\ldots J} e^{V_j}}$

For ML model, choice probability can only be obtained by simulation. For each of the normally distributed parameters ($\beta_{Purchase}, \beta_{\ln(Env)}, \beta_{\ln(Labor)}$), 10,000 draws were taken from their respective distributions. For each combination of draws, the choice probability can be calculated according to the above formula. The final choice probability is the average of these values.

For example, if a person is facing 3 alternatives (Buying jeans #1, Buying jeans #2, Not buying) and the choice probabilities are as follows:

P(Jeans #1) = 0.3; P(Jeans #2) = 0.2; P(Not buying) = 0.5

There is 30% chance that he will buy jeans #1, 20% chance he will buy jeans #2 and 50% chance that he will not buy anything. The concept of choice probability can be applied to the whole market instead of just one individual. Assuming that 100 people are considering buying a new pair of jeans and facing the above-mentioned 3 alternatives. If the calculated probabilities are the same as above, 30 people will buy the first pair of jeans, 20 people will buy the second pair and 50 people will not buy anything. Applying to our case, we can calculate the market share at each combination of attribute levels.

6.5.1 Initial scenario

We will examine 4 types of market: monopoly (no competitor), duopoly (one competitor), a market with 4 other competitors and a market with 9 other competitors. All companies are selling similar pairs of jeans. Assuming that all other factors are the same, and consumers make their decisions based on only 7 attributes (Price, Origin, Fiber, Wash, Dry, Env and Labor). There are 100,000 consumers in the market for this type of jeans, and all are women living in high-income countries. They all score 5.40 on ConcernSwt scale and 4.25 on Skepticism scale (similar to median values of background variables in our sample). The labels on all pair of jeans show that:

Price	€ 45
Country of origin	Local
Fiber	100% cotton
Washing	Machine washable
Drying	OK to tumble dry
Environment	C ★★☆☆
Labor rights	C ★★☆☆

Figure 22. Attribute levels of initial scenario

The average of our price range (€30 - €60) was chosen. A middle rating of 2 for environment and labor right ratings were used because the willingness to pay for improvement 2→ 3 is between that of 1→2 and 3→4. Other combination of ratings can be chosen as well, the calculation steps are similar.

The market share of our company in different types of market can be calculated from the formula of choice probabilities. The below table displays the market share for 4 different types of market in which there are 0, 1, 4 or 9 competitors.

Table 24. Market share at initial ratings (Env=2 and Labor=2)

Market share with initial ratings	Number of competitors			
	0	1	4	9
Env = 2 & Labor =2	22%	18%	12%	7%

When there are no other competitors in the market, our market share is 22%, the remaining 78% of consumers decide not to buy anything. This makes sense because our ratings are quite low (2 and 2). When there is 1 competitor in the market, our market share is 18%. Our market share decreases to only 12% and 7% if there are 4 and 9 other companies in the market. The more competitors exist in the market, the lower our market share is.

6.5.2 Improvement of environment rating

After a while, our company tries to become more sustainable. The environment rating on our product is improved from 2 to 3. Now our company can adopt either of the following 2 strategies:

Strategy 1: Increase the product price

From the calculated willingness to pay (Section 6.4), consumers are willing to pay €18 more for the improvement of environment rating from 2 to 3. Therefore, we can increase our price to €63 (€45 (original price) + €18), and our market share will remain unchanged. Because there are 100,000 consumers in the market, we can sell 22,000 products (22%) when there is no competitor at this higher price. This leads to an increase in sale of €18 x 22,000 = €396,000. Calculation for markets with 1, 4, 9 competitors are similar.

Table 25. Increase in sale for strategy 1 (increasing price to 63 euro)

	Number of competitors			
	0	1	4	9
Increase in sale	€396,000	€324,000	€216,000	€126,000

Strategy 2: Keep the same price to gain market share

We can also keep the price at €45. Because the environment rating gets better, our market share will increase. The new versus old market share is shown in the below table

Table 26. Market share at initial ratings (Env=2 & Labor=2) and at new ratings (Env=3 & Labor=2)

Market share with initial and new ratings	Number of competitors			
	0	1	4	9
Initial (Env= 2 & Labor=2)	22%	18%	12%	7%
New (Env=3 & Labor=2)	42%	36%	25%	17%

Our market share increases significantly for all types of markets. For example, where are no competitors, our market share almost doubles from 22% to 42%. The gain of new consumers (20% or 20,000 people) will lead to an increase in sale of 20,000 x €45 = €900,000. Calculations for markets with 1, 4, 9 competitors are similar.

Table 27. Increase in sale for strategy 2 (keeping price at 45 euro)

	Number of competitors			
	0	1	4	9
Increase in sale	€900,000	€810,000	€585,000	€450,000

Comparing the increase in sale, strategy 2 is more profitable than strategy 1 in all types of markets.

6.5.3 Improvement of labor rights rating

Similar to environment rating, if our company improves its labor rights rating from 2 to 3, it can generate a substantial increase in sale too. Again, 2 strategies can be deployed.

Strategy 1: Increase the product price
Willingness to pay for improving labor rights rating from 2 to 3 is €17, so the company can increase the price to €62 (€45 + €17) without losing market share. Because the willingness to pay for environment and labor rights rating are similar to each other, the increase in sale when labor rights rating goes up is also roughly the same as that when environment rating improves.

Table 28. Increase in sale for strategy 1 (increasing price to 62 euro)

	Number of competitors			
	0	1	4	9
Increase in sale	€374,000	€306,000	€204,000	€119,000

Strategy 2: Keep the same price to gain market share
The company can also keep the price at €45, which results in new market gain.

Table 29. Market share at initial ratings (Env=2 & Labor=2) and at new ratings (Env=2 & Labor=3)

Market share with Initial and new ratings	Number of competitors			
	0	1	4	9
Initial (Env= 2 & Labor=2)	22%	18%	12%	7%
New (Env=2 & Labor=3)	43%	37%	27%	18%

As a result, sale will increase.

Table 30. Increase in sale for strategy 2 (keeping price at 45 euro)

	Number of competitors			
	0	1	4	9
Increase in sale	€945,000	€855,000	€675,000	€495,000

Again, strategy 2 is far more profitable than strategy 1.

In conclusion, when the company improves either their environment or labor rights rating, they can increase their sale by either increasing the price or gaining new market share. If they improve both ratings further, the increase in sale will be even larger. Then the company can compare this increase in sale with the associated cost (to change their operations to improve environment and labor rights rating, to hire more employees to support a larger market, etc.)

CHAPTER 7. CONCLUSIONS, DISCUSSION, RECOMMENDATIONS AND LIMITATIONS

7.1 CONCLUSIONS

The main research question of this thesis is:

"How do fashion consumers trade off price against environment rating and labor rights rating when making their purchasing decisions?"

To answer the main research question, three sub-questions have been addressed:

Sub-question 1: To what extent do price, environment rating and labor rights rating influence fashion consumers' choices?

According to the data analysis results, all 3 attributes Price, Environment rating (Env), Labor rights rating (Labor) have a significant influence on the utility of choice alternatives, and thus consumers' choices. The higher the utility, the more likely an alternative is chosen. Price has a negative relationship with utility, meaning that consumers prefer lower price to higher price. Conversely, both Env and Labor make positive utility contributions. Therefore, higher ratings of environment and labor rights are preferred to lower ratings. The direction of the influence is consistent with our expectation.

While the contribution of Price is linear (each equal increment in price leads to an equal decrease in utility), the relationship of Env and Labor with utility is proved to follow the law of diminishing marginal utility. Utility difference will decrease when the ratings increase more and more. In other words, an increase from rating 1 to 2 will generate more utility than an increase from rating 2 to 3, which in turn generates more utility than an increase from rating 3 to 4. As a result, consumers are more sensitive to the increase from a low rating (1) than from a relatively high rating (3). It is reasonable for consumers to care more about the improvement of a badly performing product (in terms of sustainability) than the further improvement of a product that is already quite sustainable.

The 2 ratings for environment and labor rights are constructed on the same scale, so it was also tested whether consumers add the 2 separate ratings into a single composite rating when making their choices. The difference is not significant enough to prove that the composite rating was used. At the end, the model with separate ratings were chosen due to its better model fit.

While Price does not interact significantly with either of the 2 ratings, the interaction between Env and Labor is statistically significant (in model MNL-8). The sign of interaction parameter is positive, meaning that these 2 ratings inter-strengthen the importance of each other. A higher environment rating makes the labor rights rating more important and vice versa. However, in the final model (panel ML), the t-ratio of this interaction was not high enough (the threshold is 1.96 at 5% significance level), so the Env*Labor interaction was eliminated from the estimation at the end.

These 3 attributes (Price, Env, Labor) have the largest utility contribution range among the 7 main attributes, leading to their high relative importance. According to the best-fitted model (panel ML), Env and Labor are the 2 most important attributes with about 30% of relative importance each for a typical respondent in our sample. Price is the 3rd most important attribute with 19%. The other 4 attributes in the study (Origin, Fiber, Wash, Dry) have remarkably lower importance with about 1%-12% each. It can be said that in our survey, out of 7 attributes provided on the labels, respondents care about environment rating, labor rights rating and price the most when making their decisions.

It is also important to note that relative importance is not absolute but depends on the range of attribute values. The calculated relative importance in this thesis is valid for the range of attribute values used in our survey. If a different range is chosen, the results will be different. For example, price may become the most important attribute if we choose a wider price range such as €30 - €90 instead of €30 - €60.

Sub-question 2: To what extent do background variables moderate the effects of price, environment rating and labor rights rating on fashion consumers' choices?
12 background variables are studied in this thesis: 6 sociodemographic (Gender, Age, Education, Nationality, Residence, Income), 3 spending habit (Clothes, JeansFreq, JeansPay) and 3 attitudinal (ConcernEnv, ConcernSwt, Skepticism).

7 out of 12 background variables (Gender, Education, Nationality, Residence, JeansPay, ConcernSwt and Skepticism) modify the importance of Price, Env or Labor. In the final panel ML model, 4 moderating effects remained significant: Gender and Residence influence the importance of Price, whereas ConcernSwt and Skepticsm affect the importance of Labor:

- **Gender*Price**: women care more about price than men.
- **Residence*Price:** residents in high-income countries care more about price
- **ConcernSwt*Labor:** people who are more concerned about sweatshops care more about labor rights rating
- **Skepticism*Labor:** people who are more skeptical of eco-labels care less about labor rights rating

It is important to note that these 4 interactions do not change the parameter sign of Price and Labor. The parameter of Price is negative on the full range of Gender and Residence, meaning that lower price is preferred by all groups of respondents (men and women; high-income and low- & middle-income country residents). The parameter of Labor is positive on the full range of ConcernSwt and Skepticism, meaning that all respondents in our survey prefer higher labor rights rating no matter how much they are concerned about sweatshops or skeptical of eco-labels. In brief, the moderating effects of background variables do not change the direction of the main effects.

Sub-question 3: How much are fashion consumers willing to pay for improvement in environment rating and labor rights rating?
A typical respondent in the survey (with median values of background variables: female, living in high-income country, ConcernSwt = 5.40 and Skepticism = 4.25) is willing to pay €12-€36 for 1-point improvement of environment rating or labor rights rating. In other words, an increase of €12-€36 in price can be offset by a 1-point increase of either rating, leading to no change in preference for the consumer. Therefore, the company can charge €12-€36 for their product without losing this customer. On the macro-scale, they can charge this price premium without losing their market share.

The willingness to pay for environment improvement is roughly the same as that for labor rights improvement. This result is not surprising since the parameter of Env and Labor have similar size in the first models (MNL-5 and MNL-7). When interactions are taken into account (panel ML), the size of parameters is still roughly the same for a typical respondent, as proven by the similar relative importance of Env and Labor (about 30% each).

The willingness to pay for improvement in ratings is the highest when the initial rating is low (1), and the lowest when the initial rating is already high (3). This is consistent with the law of diminishing marginal return. People care more about the ratings when the ratings are very low, and care relatively less when the ratings are already quite good. To illustrate, a typical consumer in our study is willing to pay €35-€36 when the rating improves from 1 to 2. They are willing to pay only half of that amount (€17-€18) for a change from 2 to 3 of the rating. Finally, for the improvement of rating from 3 to 4, the willingness to pay is only €12.

Because 4 interactions remained significant in the panel ML model, the full parameter of Price is a function of Gender and Residence, and the full parameter of Labor is a function of ConcernSwt and Skepticism. As a result, willingness to pay for environment improvement also depends on Gender and Residence whereas the willingness to pay for labor rights improvement depends on all these 4 background variables. Women are more sensitive to Price, so their willingness to pay for the increase in either rating is lower than men. People living in high-income country are more sensitive to Price, so their willingness to pay is lower than that of low- & middle-income country residents. Someone with a higher ConcernSwt score (more concerned about sweatshops) will be willing to pay more for labor rights improvement. Someone with higher Skepticism score (more skeptical of eco-labels) will have a lower willingness to pay for labor rights improvement.

Applying the results of willingness to pay, sustainable companies can determine the price premium for superior environment and labor rights ratings of their products. They can adopt either one of two strategies: charge the price premium (willingness to pay) or keep the same price to gain market share. Assuming a market of 100,000 consumers where all companies have the median values for 7 main attributes, it has been shown that both strategies will generate significant increase in sale. When all other companies in the market have a rating of 2 for both Env and Labor, a company with a rating of 3 for either Env or Labor can gain about €100k-€400k in sale (depending on the number of competitors in the market) if they charge the price premium. If they choose to keep the same price, they will get an increase in sale of roughly €500k-€900k. These results prove that even a small willingness to pay of €17-€18 for sustainability improvement in each item could lead to a substantial economic benefit for the company when we take the number of customers in the market into account. Therefore, an accurate estimation of willingness to pay is highly important for sustainable fashion brands.

7.2 DISCUSSION

7.2.1 Methodology

Discrete choice model was chosen as the main research method which aims to measure consumers' behaviors and not just their value or attitude. This method can provide a quantitative estimation of consumers' willingness to pay for improvement in sustainability attributes, which is our main goal. Discrete choice model has several advantages which are necessary for this study. It helps to avoid judgment bias and prevent respondents from giving socially desirable answers. Both MNL model and ML model were tested in this project. MNL model is simpler, has faster estimation time and leads to easier economic appraisal. However, MNL model fails to capture nesting effect, taste heterogeneity and panel effect because it assumes that there is no correlation between similar alternatives, that every single individual attach the same importance to each attribute and that choices made by the same person are independent from each other. Despite involving more complicated calculation and requiring longer computing time, panel ML model can resolve these issues by incorporating the above-mentioned effects and heterogeneities into the utility function. In fact, our results have shown that panel ML model has a significantly better model fit than MNL model. Since we have only 7 main attributes and 12 background variables, the computer time was not excessively long. On average, each MNL model estimation took only 1-2 minutes and each ML model took about 20-25 minutes.

To collect data for the discrete choice models, a stated choice experiment was constructed. Because a hypothetical rating system for environment and labor rights is included, stated choice experiment is the appropriate method. Revealed preference, which solicit information from consumers' actual purchasing behaviors, cannot measure the effect of non-existing attributes such as our 2 ratings. Even though the environment rating and labor rights rating are not present in the current market, our hypothetical choice sets still manage to convince the consumers to use these 2 ratings to make their decisions, which was proven by the statistical significance of the parameters for the 2 ratings in the model estimation results. If the respondents had not understood the meaning of these ratings, their choices would not have been affected by them, and the parameters would have been insignificant.

Other main attributes and background variables were carefully chosen based on the currently available information on clothing labels and literature. Several background variables were proved to have a significant influence on the inclination to purchase as well as the importance of main parameters. Overall, there was a good balance between achieving better model fit with more variables and not overwhelming survey respondents with too many questions.

Sequential method was used because our choice set includes only unlabeled alternatives. Despite not controlling for orthogonality of inter-alternative attributes, the correlations among them were not too high (Appendix B). Choice sets with dominant alternatives were removed to improve standard errors. After removing 8 choice sets with dominant alternatives, the correlations were checked again. None of the correlations were problematically high. These results gave more confidence in using the generated experimental design to collect data. The final experimental design consisted of 24 choice sets which were divided into 2 blocks, so each respondent needed to make only 12 choices. This was a reasonable number of choice sets.

7.2.2 Data collection

The explanation of the attributes in the survey was concise but sufficient. How to explain the environment rating and labor rights rating, which was hypothetical and thus totally new to respondents, required special attention. Trying not to overwhelm the survey participants with too much information yet still make them understand the meaning of the ratings, the explanation was carefully constructed. First, the explanation emphasized that these ratings are compulsory (by the government), objective (rated by a 3rd party organization) and standardized (the same scale for all products in the market). A visualization of the whole scale (from best to worst) was also included. Finally, some brief examples of environment and labor rights issues in fashion industry was mentioned in the explanation to help respondents understand how the products are rated.

Two versions of the survey were quite evenly distributed. Regarding the distribution of sociodemographic background variables, some particular patterns were noticed. The majority of respondents are relatively young (over 70% are under 30 years old), highly educated (30% have a Bachelor degree and 50% have a Master degree), and on the lower side of the income spectrum (more than 40% made less than €10,000 a year). This skewed distribution of sociodemographic variables may have some influence on the results. When testing separately, none of these 3 variables (age, education, income) affect the inclination to purchase, and the only significant interaction is between education and environment rating (higher education levels increases the importance of environment rating). In the final model (panel ML), no main or interaction effects of age, education and income are significant. In the future, data from other samples with different distribution of sociodemographic variables can be collected to compare the results.

No abnormal pattern of 3 spending habit variables was observed. In terms of 3 attitudinal variables, concern about the environment and skepticism of eco-labels provide similar distribution to prior research. The only issue is that concern about environment is very skewed to the high side (the median is 6.67 on a 7-point scale). Therefore, this variable does not provide much variation among the respondents. When testing for interaction, concern about environment does not interact significantly with any of the main attributes. In future research, a different environmental concern scale that involves more variation among different people may be used.

7.2.3 Results

Alternative-specific constant (ASC)
ASC represents the base utility compared to the opt-out alternative (The utility of opt-out alternative is fixed at 0). ASC captured the tendency to purchase, which is due to other factors not included in the model. If ASC is positive, respondents always choose to purchase and do not opt out. If ASC is negative, people have a strong tendency not to purchase.

All our estimated models involve a significant and negative ASC. The negative sign of ASC proves that respondents are generally inclined to not purchase. In fact, in about 50% of our observations, the respondents chose not to buy any pairs of jeans. Only when a particular combination of attribute levels generates higher utility than the size of this constant, the respondent will choose to make the purchase. Otherwise, the opt-out option has a higher utility and will be chosen.

In panel ML model, the value of ASC is equal to -5.302, which is larger (in terms of absolute value) than utility ranges of all 7 main attributes for a "median" respondent. The 2 most important attributes with the largest utility range are Env and Labor. Their utility range is roughly 3.4 each, which is only 65% of the size of ASC. It can be said that the tendency to not buying exerts even a stronger influence than the 2 most important attributes on respondents' choices.

Table 31. ASC and utility range of main attributes
(in panel ML model with median values of background variables)

Attributes	Estimated parameter	Utility range
ASC	-5.302	-5.302
Price	-0.069	2.080
Origin	0.221	0.221
Fiber	0.492	0.492
Wash	1.311	1.311
Dry	0.074	0.074
Env	2.486	3.447
Labor	2.416	3.350

Let us assume that there are 2 choices in the market: opt-out (not buying) and buying a pair of jeans with the best levels of all 7 main attributes (€30, produced locally, 100% cotton, machine washable, tumble dryable, environment rating = 4, labor rights rating =4). The systematic utility of opting out is 0 and the systematic utility of buying that "perfect" pair of jeans (for the "median" individual) is calculated to be 3.228. Applying the formula to compute probability from systematic utility, the probability of opting out is estimated to be 4% and the probability of buying is 96%. Even when that “perfect” pair of jeans (with the best combination of attribute levels) is the only available purchase option in the market, there are still 4% of customers who decide to not buy it. It is important to note that the context in our survey is quite urgent (buying a pair of jeans for group photos with friends during a trip starting tomorrow), yet 4% of people still do not purchase when presented with the best pair of jeans, confirming the strong influence of ASC once again.

These results revealed the importance of ASC in affecting respondents’ choices in our survey, and hence their relatively strong tendency to opt out. There are several possible reasons for this pattern. First, the respondents might already have some suitable pairs of jeans at home. Second, some people might not care much about clothes during vacation or not interested in group photos, so they might not feel the need to buy a new pair of jeans just for a short trip. Moreover, respondents are limited to only 2 alternatives in each choice set, which may be too few. In some choice sets, both alternatives have low ratings or both prices are on the high side. In real life, consumers have many more choices, and they will not purchase until they find something that must be both cheap and highly rated.

Attributes

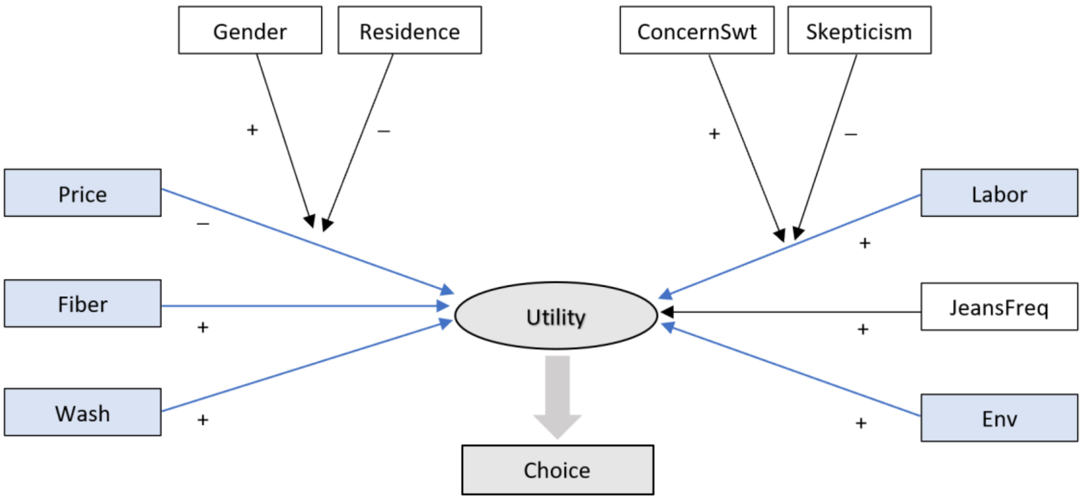


Figure 23. Diagram of relationship among variables in the final model

Main effects of main variables

5 out of 7 main variables (Price, Fiber, Wash, Env, Labor) have a significant influence on utility and subsequently people’s choice. If the influence is positive (i.e. having a positive parameter), higher values of that attribute contribute more to utility, meaning that people prefer a higher value. If the influence is negative (i.e. having a negative parameter), lower values of that attribute contribute more to utility, meaning that people prefer a lower value.

The negative sign of the price parameter indicates that people prefer lower price. The parameters of the other 4 attributes (Fiber, Wash, Env, Labor) are positive, so people prefer higher values of these attributes. In other words, 100% cotton jeans, machine-washable option, higher environment rating and higher labor rights rating are preferred. The preferences for lower price and better sustainability attributes have been confirmed in various studies (Homburg et al., 2010; Janßen & Langen, 2017) as well as consistent with our expectations. The specific preferences for pure cotton jeans and machine-washable option have not been studied by prior literature, but they do not contradict the common sense. The remaining 2 variables (Origin and Dry) do not affect utility significantly.

Main effects of background variables
7 out of 12 background variables (Gender, Residence, Clothes, JeansFreq, JeansPay, ConcernEnv, ConcernSwt) influence the inclination to purchase. If the parameter of a background variable is positive, higher value of that variable makes people more inclined to buy. If the parameter is negative, higher value of that variable makes people less inclined to buy.

First, the positive sign of the parameter of Gender variable shows that men are more inclined to purchase, probably because men usually spend less time on shopping for clothes and want to make a decision quickly whereas women are likely to postpone their purchase and check for more options. Second, parameter of Residence is negative, suggesting that people living in high-income countries are less inclined to purchase. Residents in high-income countries may have higher standards for clothes, so they are pickier and more likely to opt out when both alternatives in the choice sets are below their standards. Third, people with a higher budget for clothes are more likely to purchase. Similarly, people who buy jeans more often are more likely to choose the purchasing alternative (instead of opting out). These 2 effects are totally reasonable. Next, people who usually pay more for a pair of jeans, showing that they are willing to spend more on fashion, are more inclined to purchase. Finally, people who are more concerned about the environment and sweatshops are less likely to purchase. These people are probably more aware of the environmental and social impacts of their clothing purchase, so they try to not buy too many clothes.

Table 32. Estimated parameters and robust t-ratios of main effects of background variables (when added together to the model)

Background variable	Estimated parameter	Robust t-ratio
Gender	0.3114	2.42
Residence	-0.4980	-2.81
Clothes	0.0088	4.11
JeansFreq	0.5883	4.28
JeansPay	0.0009	0.32
ConcernEnv	-0.1708	-1.90
ConcernSwt	-0.0256	-0.43

The t-ratios of the above-mentioned 7 background variables can be used to compare the strength of their effects. Clothes and JeansFreq have the highest t-ratios, suggesting that they exert the strongest influence on the inclination to purchase. In other words, whether people opt out or not depends mostly on how much they spend on clothes and how often they buy jeans. In contrast, JeansPay and ConcernSwt have the lowest t-ratios, so we can say that the inclination to purchase is less affected by how much people pay for a pair of jeans and how much they care about sweatshops (compared to the other 5 background variables). In the final Panel ML model, only the effect of JeansFreq remained significant (as shown in figure 23).

Interactions
In terms of interaction between background variables and main attributes, 4 background variables (Gender, Residence, ConcernSwt and Skepticism) have a significant effect in the final model. Price is more important for women (versus men) and for high-income country residents (versus those living in low- & middle-income countries). Labor rights rating is more important for those who care more about sweatshops and for those who are less skeptical of eco-labels.

Regarding the influence of Gender and Residence on the importance of Price attribute:

- For people living in middle- or low-income country, the parameter of price for women is -0.034 and for men is -0.008.
- For people living in high-income country, the parameter of price for women is -0.069 and for men is -0.043.

The importance of price for women is about 2-4 times higher than that for men, meaning that that women are more sensitive to price than men. This pattern agrees with prior literature (Mohammadian, 2004) as well as various surveys studying gender difference in consumption of several types of goods. Women are more likely to compare price before purchasing and also more inclined to shop at discount retail shops (Petro, 2018). Another survey showed that women are 19% more likely to make a purchasing decision based on price (Munbodh-LE, 2014). There are several possible reasons for this. Women generally spend more time on shopping, so they may not mind looking for as many options as possible. Women also buy more pieces of clothes, so with the same budget, women need to scrutinize the price of each piece more thoroughly.

Regarding the country of residence, residents in high-income counties care more about price than those in low- & middle-income countries. This is contradicting with the general perception that high-income country residents have higher income, so they should be less sensitive to price. However, it is important to note that Income variable does not interact significantly with Price, so Income is not the main factor behind the Residence*Price interaction. The higher importance of price among residents in high-income countries are due to factors beyond income. More studies are required to understand the reason behind this.

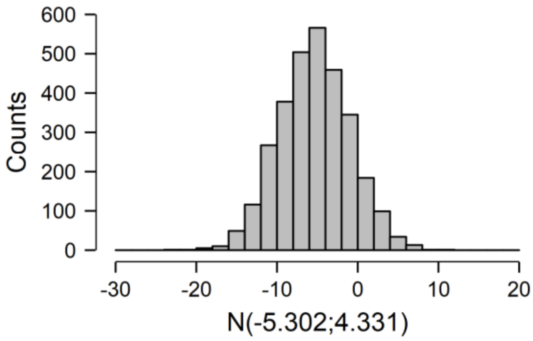
With respect to the ConcernSwt*Labor interaction, people who are more concerned about sweatshops care more about labor rights rating, implying that those who score higher on ConcernSwt scale are also willing to pay a higher price for labor rights improvement. Our scale for ConcernSwt is adopted from Phau et al (2015). In their study, concern about sweatshops leads to lower intention to buy sweatshop products and higher willingness to pay for products not make in sweatshops.

Next, the interaction effect of Skepticism is analyzed. When tested individually, Skepticism variable has a significant interaction with all 3 main attributes (Price, Env, Labor). People who are more skeptical of eco-labels care more about price and care less about both ratings. However, in the final model, only the interaction with labor rights rating remained significant enough. Due to this interaction, those who have higher doubt of eco-labels will have a lower willingness to pay for improvement in labor rights rating.

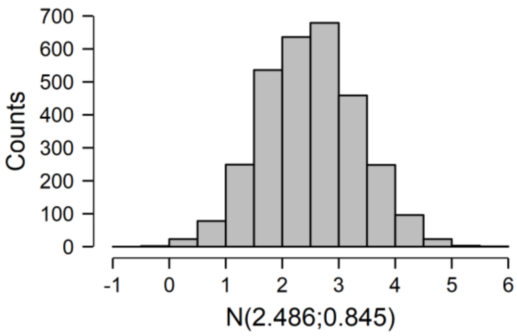
Heterogeneities

In the panel ML model, the sigmas for environment rating and labor rights rating are significant, meaning that people attach different levels of importance to environment rating and labor rights rating when making their choices. The inclination to purchase is also significantly different among people. In MNL models, this inclination is assumed to be the same, which is captured in the alternative-specific constant. In ML model, that value is not a constant anymore but varies from one person to another. Capturing these differences helps to explain the variation in dataset better. Meanwhile, sigma for price is not significant, meaning that the importance of price is roughly the same among the respondents. The below distribution plots visualize the heterogeneities of purchase tendency, taste for environment rating and taste for labor rights rating.

a) Purchase heterogeneity: $\upsilon_{\text{Purchase}}$



b) Taste heterogeneity for environment rating: $\beta_{\ln(\text{Env})}$



c) Taste heterogeneities for labor rights rating: $\beta_{\ln(\text{Labor})}$

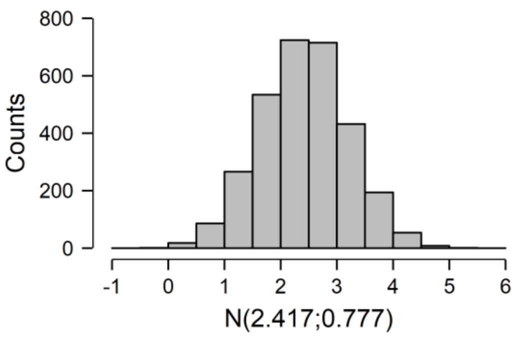


Figure 24. Distribution plots of parameters of purchase inclination, environment rating and labor rights rating (with mean and sigma of the normal distribution)

Purchase heterogeneity is $\upsilon_{\text{Purchase}} \sim N(-5.302, 4.331)$. The sigma is about 80% of the mean value, indicating that the inclination to purchase varies very widely among the individuals. Besides, the probability of $\upsilon_{\text{Purchase}}$ being positive is about 0.11, meaning that roughly 11% of population will have a positive inclination to purchase. This group of people are highly inclined to purchase and will not choose the opt-out option.

Taste heterogeneity for environment rating is $\beta_{\ln(Env)} \sim N(2.486, 0.845)$. In this case, the mean value is almost 3 times as high as the sigma. The probability of $\beta_{\ln(Env)}$ being negative is almost 0, meaning that almost all people will have a positive parameter for environment rating.

Taste heterogeneity for labor rights rating is $\beta_{\ln(Labor)} \sim N(2.417, 0.777)$ (the mean value includes interaction effects with ConcernSwt (median = 5.40) and Skepticism (median = 4.25)). Again, the mean value is over 3 times as high as the sigma, so the probability of $\beta_{\ln(Labor)}$ being negative is almost 0. Almost everyone has a positive labor rights parameter.

Therefore, it can be said that everyone prefers higher environment rating and higher labor rights rating.

Model fit

Table 33. Model fit of the models in this study

Model	MNL-5	MNL-7	MNL-8	Panel ML
Final-LL	-1277.403	-1226.004	-1199.295	-943.8916
Adj. Rho-square	0.2073	0.2365	0.2487	0.4080
Parameters	8	12	19	16

It can be seen from the above table that the biggest change in model fit occurred when we moved from MNL-8 to ML model. Among the 3 MNL models, adding background variables and interactions improved the Rho-square by about 3-4%. Adding heterogeneities and panel effect increased the Rho-square by almost 16% even though panel ML had 3 fewer parameters than MNL-8.

Comparing our best model (panel ML), which include background variables, interactions, heterogeneities, and panel effect, with the original model (MNL-5), the adjusted Rho-square improves remarkably from about 0.21 to 0.41. The final panel ML model can explain about 41% of variation in the dataset, which is twice as high as MNL-5 (about 21%). With the adjusted Rho-square of roughly 0.41, the panel ML model has a highly good model fit (McFadden, 1977).

Comparing the log-likelihood also shows the superior model fit of panel ML model. MNL-5 includes 8 parameter and has a log-likelihood of -1277.403 while panel ML model involves 16 parameters with a log-likelihood of -943.892. The LRS is 667.022, which is far larger than the threshold value of 20.09 for 8 degree of freedom at 1% significance level. Therefore, panel ML model is significantly better. There is almost no chance that the better model fit of panel ML model is due to randomness.

Adding background variables, interactions, heterogeneities and panel effect (especially the last two) helped to generate a much better model fit to explain the variation in our dataset. The Rho-square is also within the range for a good fit, providing more confidence in using panel ML model to calculate willingness to pay and choice probabilities.

Willingness to pay

Because the taste heterogeneities of environment rating and labor rights rating are significant, willingness to pay was estimated by simulation instead of direct calculation. The simulation showed that willingness to pay for environment rating and labor rights rating also followed a normal distribution like the price parameter and labor rights parameter. A "median" respondent was willing to pay €12-€36 on average for a 1-point improvement in either rating. The range from 10^{th}-percentile to 90^{th}-percentile was about ±40%

of the average value. Considering the fact that over 70% of respondents in our survey usually paid about €10-€50 for a pair of jeans and most jeans on Zara and H&M websites cost about €30-€60, our calculated willingness to pay is roughly 50%-100% of the price of one pair of jeans. In other words, instead of buying 2 (or 3) pairs of less sustainable jeans, the respondents are willing to buy only 1 (or 2) pair if either environment rating or labor rights rating is improved by 1-point.

No prior research used an objective rating scale for sustainability like this study, so no comparison is possible. However, the values of willingness to pay seem to be reasonable. Willingness to pay for other significant main attributes (Fiber and Wash) can also be calculated to check whether there are any abnormal values. The "median" respondent is willing to pay €7 more if the fiber content changes from 80% cotton to 100% cotton, and €19 more if the pair of jeans is machine-washable instead of requiring hand-washing. Again, these values are within the price range of a typical pair of jeans in the market.

7.3 RECOMMENDATIONS

7.3.1 Business: Strategies of sustainable fashion brands

The theory of innovation diffusion, which was briefly mentioned in **Chapter 2 (Problem analysis)**, states that innovative products need to spread from niche markets to the mass population in order to be the market leader. The innovation needs to pass from one consumer group to another sequentially. First, the new product needs to capture the attention and convince the innovators, then the early adopters to purchase. After that, it needs to spread to the majority of the population (early majority then late majority). The last group to adopt an innovation is called laggards.

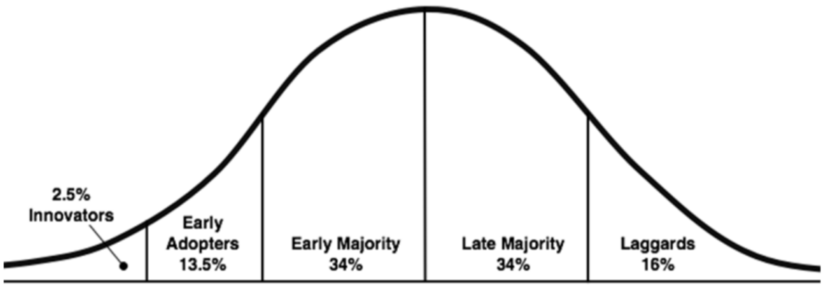


Figure 25. Diffusion of innovation

Currently, less than 20% of the fashion market belongs to sustainable brands (Kaucic & Lu, 2019), so the spread of sustainable fashion is likely to be still in the early adopters group. To attract the early majority group, pricing is very important. This research has shown how sustainable fashion brands can estimate consumers' willingness to pay for better sustainability ratings. After that, they can determine whether they want to charge a price premium equal to consumers' willingness to pay or keep the same price as competitors to gain new customers. The lower the price, the higher the market share. Both strategies have their own pros and cons. Comparing potential increase in sale and the incurred cost, each brand needs to estimate at which price and market share their profit is optimal.

If a sustainable fashion brand chooses to charge higher price (strategy 1), they will be likely to cover all their cost and gain quick profit in the short term, providing enough cashflow for their operations. This strategy is probably suitable for new and small companies which usually face the problem of limiting capital. Running out of cashflow is a common financial issue for many start-ups even though their business models can be hugely profitable (Deeb, 2013).

If the brand chooses to charge the same price as their competitors (strategy 2), they need to have a strong financial status to offset some losses in the short term. Producing clothes in a more sustainable way probably requires higher cost than fast fashion. To keep the price at the same level as fast fashion competitors, the sustainable brand is willing to give up profit at the moment in order to build up their customer base. Our simulation in chapter 7 has shown that keeping the same price creates a sale increase that is 2-4 times as high as that when charging higher price. Once the company becomes popular enough in the mass market and has a loyal group of customers, they can start to charge higher price. In the long run, the obtained larger market share will gradually generate profit. This strategy is popular with start-ups that have strong back up from their investors. For example, Uber deployed various aggressively competitive pricing programs and promotions to attract more customers in the fight with traditional taxis and other car-pooling apps. In 2019, the company had a loss of $8.5 billion (Hawkins, 2020). Sustainable fashion brands will hardly get the same amount of capital as a technology company like Uber, so they need to be very careful with how they price their products. This strategy has higher risks, but also higher profit in the long term.

Another problem that needs to be solved is related to the use of technology. Currently, most technological innovations focus on improving the environmental impact whereas the social impact is rarely addressed. Sustainable fashion brands should also try to adopt new technologies such as blockchain to enhance transparency of their supply chain, ensuring the labor rights of all workers who make their clothes. This study has showed that labor rights has an equal importance as environment. An improvement in labor rights rating can generate as much revenue as a rise in environment rating.

7.3.2 Societal: The role of government

Traditionally, government is thought as the important intervening force when the market cannot adjust itself to give higher overall welfare. Regarding sustainability issues of fashion industry, the government can introduce appropriate policies to enhance environmental protection and labor rights of workers. For example, the European Union (EU) has a regulation called REACH (Registration, Evaluation, Authorization and restriction of CHemicals) to limit the use of some chemicals in textile and leather production. Switzerland also has a similar regulation called ORRChem (Chemical Risk Reduction Ordinance). In terms of labor rights, there are several non-legal but mandatory requirements for clothes sold in European markets such as BSCI (Business Social Compliance Initiative) or WRAP (Worldwide Responsible Accredited Production) (CBI, 2020). In the study of Fashion Revolution (2018), 68% of respondents said that the government should regulate apparel production to ensure their sustainability, and about 62-77% agreed that fashion companies should be mandated by law to protect the environment, respect human rights and provide fair living wage for their workers.

This study has demonstrated another role of the government in improving the sustainability of fashion industry. 68-72% of surveyed respondents felt that the government must require apparel companies to provide information related to environmental and social impacts of their products (Fashion Revolution, 2018). It is high time the government mandated the use of a standardized objective rating system on clothing labels. The rating provides consumers with necessary information to make informed decisions. Currently, it is difficult to recognize which products are truly sustainable and which brands engage in greenwashing. A wide range of claims and graphics used by different companies can also confuse consumers. Therefore, the government should mandate the use of a single rating system on labels which are verified by governmental agencies themselves or by third-party organizations.

Another important benefit of the rating system is that it can help sustainable companies to quantify consumers' preferences for their higher sustainability ratings. They will be able to estimate willingness to pay and charge their products accordingly to compete with fast fashion.

As discussed throughout this report, sustainability rating on clothing should cover both environmental and labor rights aspects. The government can require 2 separate ratings to be put on the labels or a single rating that takes both environment and labor rights into account. The ratings can be constructed as the weighted average of several indicators, each of which focus on a sustainable issue of clothing production and consumption. The following table provides an example list of questions to construct some potential indicators.

Table 34. Example of indicators for sustainability ratings

Rating	Indicator	Description
Environment	Sustainability of fiber	How much water is consumed to produce 1kg of fiber? How much wood is required to produce 1kg of fiber? Does fiber production involves cutting down of ancient and endangered forests? Does fiber production degrade soil quality? How much microplastic is released to water sources during the lifespan of 1kg of fiber?
	Chemical use	How much chemical is used to generate a garment? How toxic are the chemicals to human? How toxic are the chemicals to the ecology (including aquatic life)?
	Waste and discharge	How much solid waste is generated to produce a garment? How much liquid effluent is generated to produce a garment? Is the effluent treated before discharge? How much of unsold clothes is disposed by the company? What disposal method is used (burning, burying, etc.)? How much packaging is used for shipping and selling? Are the clothes and packaging materials bio-degradable?
	Carbon emission	What kind of energy source is used in factory? How much emission is created for producing a garment (from fiber production to garment assembly)? How much emission is created for shipping a garment to the selling destination? How much emission is created by other supporting activities (eg. returning clothes)?
	Recycling program	Does the brand have a program for customers to donate old clothes? How much waste is recycled throughout the supply chain? How much of unsold clothes is recycled?
Labor rights	Supply chain transparency	Does the company have information about all their suppliers (fiber, chemicals, etc.) and distributors? Do they audit the sustainable performance of these suppliers and distributors?
	Sufficient living wage	How much are workers paid? Is it above the living wage threshold in their corresponding country?

	Limit working hours	How many hours does a worker work per week on average? What is the limit of working hours per week? Are workers forced to work overtime against their will?
	Pay for overtime	How much are workers paid for overtime work?
	Working conditions	How often do they check and identify potential hazards? What is the severity of physical, chemical, biological hazards in the working environment? What is the likelihood that workers get exposed to these hazards? Are these hazards regularly evaluated and properly mitigated?
	Safety and health program	Do they have a program to maintain and audit the safety of building/factory? Do they have a health check-up program for workers in high risk tasks? Do they provide adequate insurance cover for job-related accidents and illnesses?
	Presence of union	Are workers allowed to form union? Are the leaders of unions appointed by an appropriate method (not forced by management)? How often does union have meetings with workers and management? How often are union's recommendations approved or rejected? What are the reasons?
	Child and forced labor	Are there child labor or forced labor in the entire supply chain? What have the company done to check and prevent these issues in their foreign factories?
	Abuse and discrimination	Are there incidents related to abuse and discrimination? Does the company adopt a fair-opportunity employment policy? Does the company have any organizations/policies to protect and promote the welfare of minority and vulnerable groups?

7.4 LIMITATIONS AND FUTURE RESEARCH

The first limitation of this study is the number of respondents. Due to time and resource constraints, this thesis managed to collect data from 123 people. Even at such a number of respondents, only 4 interactions remained significant in our final model even though 11 interactions were significant when tested individually. A larger sample will allow testing for more variables, including more variable levels as well as keeping more interactions in the final model.

The second limitation is the sample characteristics. The data was collected by convenience sampling. As a result, majority of respondents are still quite young, highly educated and having low income. In general, skewed distribution of sociodemographic variables such as age, education level or income may affect the weights of attributes in the choice model and thus requires special caution when generalizing the results. For example, highly educated people are likely to care more about environment and labor right issues, causing overestimation of the parameters for these two attributes. However, our sample is quite similar to the target market of sustainable apparel brands. The results of this study are thus valid for the main customer segment of sustainable fashion. Other samples with different sociodemographic distribution can be collected to obtain insights into other market segments.

Another limitation is related to the hypothetical bias of stated choice experiments. Choosing a more expensive alternative in a hypothetical situation is very different from actually buying a more expensive piece of clothes in real life. When completing the survey, respondents did not feel the consequence of their choices because they did not need to spend their real money on the chosen pair of jeans. The choices may be very different if the consumption is observed in an actual shop. Therefore, using stated choice experiment may underestimate the importance of price. Our hypothetically constructed experiment may give a lower weight for price, and thus higher willingness to pay compared to consumers' real preference.

The context of the survey assumed that respondents checked the label only after they had chosen a pair of jeans that fitted them well and looked good of them, meaning that consumers were on the verge of purchasing. In other words, consumers always considered buying the pair of jeans even if the environment and labor rights ratings are low. In reality, many people will check the label before trying on clothes. Environment and labor rights ratings may be the preliminary criteria when choosing a piece of clothing. After that, consumers will proceed to compare other features among those choices with acceptable ratings. More survey with different contexts, which may give different attribute weights and willingness to pay, are required to gain more understanding of consumers' behaviors.

This study also assumed that all other product features (fashion-, store-, brand-related variables) are the same between the alternatives because the focus is on environment rating and labor rights ratings. Only information usually found on clothes labels are included in the experimental design. In reality, the other features are likely to affect consumers' choices as well. In future research, other experimental designs can be constructed to study these other features. If a large enough sample is collected, a large number of characteristics can be included. Which approach to follow (using only some certain variables or including as many as possible) depends on the purpose of the research.

Finally, our calculated willingness to pay seems to be on the high side. For instance, to improve environment/labor rights rating from 1 to 2, people are willing to pay more than €30, which is the maximum difference of price (€60 versus €30) in the survey. One possible explanation is that respondents were aware of the objective of the survey, so they might care more the environment/labor rights attributes of alternatives in the choice sets, leading to higher willingness to pay. Other methods to estimate willingness to pay (Breidert et al., 2015) can be adopted to confirm our results.

For example, some Revealed Preference methods such as analyzing market data or conducting experiments can be used. Market data analysis involves predicting future pattern based on past records, which include either panel data (collecting data from a group of customers) or store data (tracking sale transactions). This method assumes that the future demand will follow the same trend as the past. One potential problem is the little variation in price from the collected data. Lab and field experiment are some other options. In lab experiment, participants are given a certain amount of money and asked to buy certain combinations of products in an artificial setting. In field experiment, different attributes are varied in a test location/market, and customers' behaviors are recorded. In contrast to market analysis, attribute levels can be systematically varied in both lab and field experiment.

Other Stated Preference methods, which include direct and indirect approaches, may be tested as well. Direct approaches such as surveying experts or customers have some potential issues. Asking experts is only applicable for small markets where behaviors of consumers are well understood by experts. Asking the consumers may overestimate the importance of some variables. Consumers may also miscalculate the price or do not understand complex combinations of attributes to give an accurate estimate of willingness to pay. Despite these flaws, they can still be used to compare the results with other methods. Discrete choice model is an indirect approach, which has been used in this study. Another way to indirectly measure consumers' preferences is asking consumers to rank different alternatives in terms of their preference/attractiveness/purchase intention, etc. instead of choosing one from a choice set like in discrete choice model.

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APPENDICES

A. NGENE SYNTAX AND GENERATED EXPERIMENTAL DESIGN

```
Design
; alts = alt1, alt2 ; orth = seq ; rows = 16 ; foldover ; block = 2 ; model:
U(alt1) =
beta_price * price[30,40,50,60] + beta_origin * origin[0,1] + beta_fiber * fiber[0,1] + beta_wash *
wash[0,1] + beta_dry* dry[0,1] + beta_env * env[1,2,3,4] + beta_labor*labor[1,2,3,4]/
U(alt2) =
beta_price * price + beta_origin * origin + beta_fiber * fiber + beta_wash * wash + beta_dry* dry +
beta_env * env + beta_labor*labor $
```

**Choice sets in grey shade: removed due to dominance*

#	Price1	Origin1	Fiber1	Wash1	Dry1	Env1	Labor1	Price2	Origin2	Fiber2	Wash2	Dry2	Env2	Labor2	Block	Foldover
1	30	1	0	1	1	3	3	60	0	1	1	1	3	1	1	1
2	60	0	1	1	1	3	1	40	0	0	1	0	1	4	1	1
3	30	1	1	1	1	2	1	50	0	0	0	1	2	2	1	1
4	50	1	1	1	0	1	2	30	0	1	0	0	4	3	2	1
5	60	1	1	0	0	1	3	50	0	1	0	1	3	4	1	1
6	60	1	0	0	0	4	1	40	0	1	1	0	4	2	2	1
7	50	0	0	0	1	2	2	60	1	1	0	0	1	3	1	1
8	40	0	0	1	0	1	4	30	0	0	1	1	4	2	2	1
9	30	0	1	0	0	4	3	40	1	0	0	1	3	2	1	1
10	40	1	0	0	1	3	2	30	0	1	1	1	1	4	2	1
11	60	0	0	1	1	2	3	50	1	1	0	1	4	1	2	1
12	40	0	1	1	0	4	2	60	1	0	1	1	1	2	2	1
13	40	1	1	0	1	2	4	40	0	1	0	1	1	1	2	1
14	50	1	0	1	0	4	4	30	1	1	0	0	3	2	1	1
15	50	0	1	0	1	3	4	50	1	1	1	0	1	2	2	1
16	30	0	0	0	0	1	1	30	1	1	1	1	2	1	1	1
17	60	0	1	0	0	2	2	30	0	0	0	0	1	1	1	2
18	30	1	0	0	0	2	4	50	0	1	1	0	2	3	1	2
19	60	0	0	0	0	3	4	50	0	0	1	0	3	1	1	2
20	40	0	0	0	1	4	3	60	0	1	0	0	2	2	2	2
21	30	0	0	1	1	4	2	40	1	1	1	0	3	3	1	2
22	30	0	1	1	1	1	4	30	1	0	0	0	2	4	2	2
23	40	1	1	1	0	3	3	60	1	0	0	0	4	1	1	2
24	50	1	1	0	1	4	1	50	1	0	1	0	4	4	2	2
25	60	1	0	1	1	1	2	60	1	1	1	1	4	4	1	2
26	50	0	1	1	0	2	3	50	1	0	0	1	1	3	2	2
27	30	1	1	0	0	3	2	60	0	0	0	0	3	4	2	2
28	50	1	0	0	1	1	3	30	1	0	1	1	3	3	2	2
29	50	0	0	1	0	3	1	40	1	1	0	1	2	4	2	2
30	40	0	1	0	1	1	1	40	1	0	1	0	2	1	1	2
31	40	1	0	1	0	2	1	60	0	0	1	1	2	3	2	2
32	60	1	1	1	1	4	4	40	0	0	0	1	4	3	1	2

B. CORRELATION AMONG ATTRIBUTES

The below tables show correlation among attributes in the generated experimental design (before and after removing choice sets with dominant alternatives). The quadratic components of Env and Labor are also included. The blue-shaded cells indicate correlation between the quadratic component and its original linear component, which is about 1 (perfect correlation) as expected.

Before removing choice sets with dominant alternative

	Price1	Origin1	Fiber1	Wash1	Dry1	Env1	Labor1	Square (Env1)	Square (Labor1)	Price2	Origin2	Fiber2	Wash2	Dry2	Env2	Labor2	Square (Env2)	Square (Labor2)
Price1	1																	
Origin1	0	1																
Fiber1	0	0	1															
Wash1	0	0	0	1														
Dry1	0	0	0	0	1													
Env1	0	0	0	0	0	1												
Labor1	0	0	0	0	0	0	1											
Square (Env1)	0	0	0	0	0	0.98	0	1										
Square (Labor1)	0	0	0	0	0	0	0.98	0	1									
Price2	-0.05	0.11	0	0.06	0.06	0.23	-0.08	0.16	-0.123	1								
Origin2	-0.06	-0.38	0	0.13	0.13	0	-0.06	0.04	-0.077	0	1							
Fiber2	0.06	0.13	-0.5	-0.13	0.13	0	0.06	0	0.033	0	0	1						
Wash2	-0.06	0	-0.38	-0.13	0.13	0	-0.22	0.02	-0.176	0	0	0	1					
Dry2	-0.06	0.13	-0.13	0.25	0	-0.22	0	-0.22	-0.022	0	0	0	0	1				
Env2	0.18	0.39	-0.17	0.22	-0.11	0.05	0.1	0.13	0.089	0	0	0	0	0	1			
Labor2	0.1	0.22	0.06	0.11	0.11	-0.03	-0.2	-0	-0.207	0	0	0	0	0	0	1		
Square (Env2)	0.26	0.39	-0.12	0.24	-0.09	0.06	0.1	0.13	0.083	0	0	0	0	0	0.98	0	1	
Square (Labor2)	0.12	0.22	0.08	0.09	0.13	-0.06	-0.23	-0.05	-0.233	0	0	0	0	0	0	0.98	0	1

All within-alternative correlation coefficients are 0, while the highest inter-alternative correlation coefficient is -0.5

After removing choice sets with dominant alternative

	Price1	Origin1	Fiber1	Wash1	Dry1	Env1	Labor1	Square (Env1)	Square (Labor1)	Price2	Origin2	Fiber2	Wash2	Dry2	Env2	Labor2	Square (Env2)	Square (Labor2)
Price1	1																	
Origin1	-0.2	1																
Fiber1	-0.03	0.03	1															
Wash1	0.05	0.03	-0.03	1														
Dry1	0.07	-0.1	0.1	-0.07	1													
Env1	0.08	0.14	0.02	-0.06	0.01	1												
Labor1	0.05	-0.07	-0.15	-0	-0.18	0.02	1											
Square (Env1)	0.04	0.13	0.06	-0.02	0.02	0.98	0.04	1										
Square (Labor1)	0.06	-0.05	-0.16	0.01	-0.15	0	0.99	0.03	1									
Price2	-0.11	0.11	0.05	-0.11	-0.08	0.19	-0.18	0.1	-0.203	1								
Origin2	-0.07	-0.41	0.07	0.07	0.17	0.23	0.04	0.27	0.006	0.16	1							
Fiber2	0.07	0.04	-0.57	-0.04	0.15	0.03	0.11	0.01	0.083	-0.17	0.19	1						
Wash2	-0.08	-0.1	-0.24	-0.24	0.16	0.09	-0.11	0.1	-0.048	0.07	-0.16	-0.02	1					
Dry2	-0.05	-0.03	-0.14	0.37	-0.1	0.06	-0.07	0.05	-0.083	0.03	-0.07	-0.13	-0.1	1				
Env2	0.01	0.35	-0.06	0.23	-0.11	0.1	0.25	0.17	0.25	-0.09	-0.03	-0.06	-0.19	-0.01	1			
Labor2	-0.19	0.25	-0.01	0.07	0.2	0.12	-0.27	0.12	-0.241	-0.09	-0.12	0.14	0.05	0.01	-0.16	1		
Square (Env2)	0.11	0.34	-0.02	0.24	-0.08	0.09	0.25	0.16	0.243	-0.09	-0.03	-0.05	-0.18	0	0.99	-0.17	1	
Square (Labor2)	-0.15	0.22	0.01	0.02	0.22	0.11	-0.31	0.09	-0.279	-0.1	-0.12	0.1	0.04	-0.04	-0.15	0.98	-0.16	1

The highest within-alternative correlation coefficient is 0.19, while the highest inter-alternative correlation coefficient is -0.57. No correlations are problematically strong (having a coefficient over 0.7).

C. SURVEY

Sustainable fashion consumption

Dear respondent,

You are being invited to participate in a Master thesis study titled "Sustainable consumption of fast fashion", which is an entirely scientific research and not commissioned by any companies or organizations.

The purpose of this study is to analyze how consumers trade off different characteristics presented on product labels when purchasing clothes. Your responses will enable the researcher to formulate data-driven recommendations regarding the sustainability of apparel production and consumption.

The survey consists of 4 parts and takes approximately 10 minutes to complete.
Please only do this survey if:
- You are at least 18 years old
- You have purchased at least 1 pair of jeans in the last 5 years.

Your participation in this study is entirely voluntary, and you can withdraw at any time. Your answers will remain confidential. NO personal data that can be identifiable to individual level is collected in this study. With starting this survey, you grant us permission to use your responses for our research.

Best regards,

Pham Dang Khoa
TU Delft, Netherlands
pham-1@student.tudelft.nl

Next

Part 1 of 4: Your general information

1. Your gender *

Female

2. Your year of birth (eg. 1985) *

Your answer

3. You highest level of education (completed or currently studying) *

Choose

4. Your country of citizenship (nationality) *

Choose

Please specify your country of citizenship if you choose "Others"

Your answer

5. Your country of residence (where you live now) *

Choose

Please specify your country of residence if you choose "Others"

Your answer

6. Your annual net income (after tax) including all types of bonus, investment, scholarship, allowance, part-time job wage, etc. (in EUR) *

Choose

Back Next

Part 2 of 4: Your spending pattern

1. Every month, how much do you spend on clothes (excluding shoes and accessories)? (in EUR) *

40 - 60

2. On average, how often do you buy jeans? *

Choose

3. On average, how much do you usually pay for 1 pair of jeans? (in EUR) *

Choose

Back   Next

Part 3 of 4: Choice task

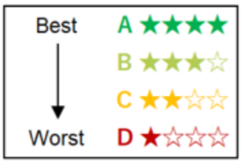
CONTEXT:

Assume that you are going on **a trip with your close friends** (3 - 5 people) **tomorrow**. Your group wants to **coordinate clothes for group photos**, and you agree on the theme of denim. Therefore, you decide to go shopping for a new pair of jeans.

You manage to find two pairs of jeans that look good on you and fit you well. You like the style, the color, and the feel when touching the fabric of both. When checking the product tags, you see the below characteristics:

- **Price** (in EUR)
- **Country of origin:**
  - ***Local*** (manufactured in the same country where it is sold); or
  - ***Foreign*** (manufactured overseas)
- **Fiber content:**
  - ***100% cotton*** (most common, more comfortable); or
  - ***80% cotton + 20% others*** (better stretching to provide tighter fit)
- **Washing instruction:**
  - ***Machine washable***; or
  - ***Hand wash only***
- **Drying instruction:**
  - ***OK to tumble dry*** (spinning in hot air in a dryer); or
  - ***DO NOT tumble dry*** (you should hang it out to dry)

- **Environment Rating** & **Labor rights Rating:** Assume that the government requires all apparel companies to put these ratings, which are given by IAF (International Apparel Federation), on their labels.



Each product is rated on a 4-point scale with A being the best and D being the worst.

Environment rating is based on the brand's *environmental* issues (Carbon emission, Use of toxic chemicals, Water pollution, Waste disposal, Lack of recycling, etc.)

Labor rights rating is based on the brand's *employment* issues (Unsafe working conditions in factories, Workers' exposure to health hazards, Insufficient wage, Child labor, Abuse & Discrimination, etc.)

TASK:

You will be presented with **12 questions.**
Each question requires you to make 2 choices:

a) Select your preferred pair of jeans out of 2 options based on the information on their product tag/label.

b) You need to decide whether you will buy the chosen pair of jeans for your trip.

Please consider these 12 questions as **independent** scenarios (eg. your choice in question 1 should not affect the choice in question 2 and so on)

1 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 60	€ 40
Country of origin	Foreign	Foreign
Fiber	100% cotton	80% cotton
Washing	Machine washable	Machine washable
Drying	OK to tumble dry	Do not tumble dry
Environment	B ★★★☆	D ★☆☆☆
Labor rights	D ★☆☆☆	A ★★★★

1 ○ 2 ○

1 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

2 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 30	€ 50
Country of origin	Local	Foreign
Fiber	100% cotton	80% cotton
Washing	Machine washable	Hand wash
Drying	OK to tumble dry	OK to tumble dry
Environment	C ★★☆☆	C ★★☆☆
Labor rights	D ★☆☆☆	C ★★☆☆

1 2

○ ○

2 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

3 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 50	€ 60
Country of origin	Foreign	Local
Fiber	80% cotton	100% cotton
Washing	Hand wash	Hand wash
Drying	OK to tumble dry	Do not tumble dry
Environment	C ★★☆☆	D ★☆☆☆
Labor rights	C ★★☆☆	B ★★★☆

1 2

○ ○

3 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

4 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 30	€ 40
Country of origin	Foreign	Local
Fiber	100% cotton	80% cotton
Washing	Hand wash	Hand wash
Drying	Do not tumble dry	OK to tumble dry
Environment	A ★★★★	B ★★★☆
Labor rights	B ★★★☆	C ★★☆☆

1 2

○ ○

4 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

5 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 50	€ 30
Country of origin	Local	Local
Fiber	80% cotton	100% cotton
Washing	Machine washable	Hand wash
Drying	Do not tumble dry	Do not tumble dry
Environment	A ★★★★	B ★★★☆
Labor rights	A ★★★★	C ★★☆☆

1 2

○ ○

5 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

6 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 60	€ 30
Country of origin	Foreign	Foreign
Fiber	100% cotton	80% cotton
Washing	Hand wash	Hand wash
Drying	Do not tumble dry	Do not tumble dry
Environment	C ★★☆☆	D ★☆☆☆
Labor rights	C ★★☆☆	D ★☆☆☆

1 ○ 2 ○

6 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

7 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 30	€ 50
Country of origin	Local	Foreign
Fiber	80% cotton	100% cotton
Washing	Hand wash	Machine washable
Drying	Do not tumble dry	Do not tumble dry
Environment	C ★★☆☆	C ★★☆☆
Labor rights	A ★★★★	B ★★★☆

1 ○ 2 ○

7 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

8 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 60	€ 50
Country of origin	Foreign	Foreign
Fiber	80% cotton	80% cotton
Washing	Hand wash	Machine washable
Drying	Do not tumble dry	Do not tumble dry
Environment	B ★★★☆	B ★★★☆
Labor rights	A ★★★★	D ★☆☆☆

1 ○ 2 ○

8 b) Will you buy the chosen jeans for you trip tomorrow? *

- ○ Yes, I will.
- ○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

9 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 30	€ 40
Country of origin	Foreign	Local
Fiber	80% cotton	100% cotton
Washing	Machine washable	Machine washable
Drying	OK to tumble dry	Do not tumble dry
Environment	A ★★★★	B ★★★☆
Labor rights	C ★★☆☆	B ★★★☆

1 ○ 2 ○

9 b) Will you buy the chosen jeans for you trip tomorrow? *

- ○ Yes, I will.
- ○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

10 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 40	€ 60
Country of origin	Local	Local
Fiber	100% cotton	80% cotton
Washing	Machine washable	Hand wash
Drying	Do not tumble dry	Do not tumble dry
Environment	B ★★★☆	A ★★★★
Labor rights	B ★★★☆	D ★☆☆☆

1 ◯ 2 ◯

10 b) Will you buy the chosen jeans for you trip tomorrow? *

◯ Yes, I will.

◯ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

11 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 40	€ 40
Country of origin	Foreign	Local
Fiber	100% cotton	80% cotton
Washing	Hand wash	Machine washable
Drying	OK to tumble dry	Do not tumble dry
Environment	D ★☆☆☆	C ★★☆☆
Labor rights	D ★☆☆☆	D ★☆☆☆

1 ◯ 2 ◯

11 b) Will you buy the chosen jeans for you trip tomorrow? *

◯ Yes, I will.

◯ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

12 a) Which jeans do you prefer? *

Characteristics	Jeans #1	Jeans #2
Price	€ 60	€ 40
Country of origin	Local	Foreign
Fiber	100% cotton	80% cotton
Washing	Machine washable	Hand wash
Drying	OK to tumble dry	OK to tumble dry
Environment	A ★★★★	A ★★★★
Labor rights	A ★★★★	B ★★★☆

1 ○ 2 ○

12 b) Will you buy the chosen jeans for you trip tomorrow? *

○ Yes, I will.

○ No, I won't. (Therefore, I won't have new jeans for group photos during the trip).

Part 4 of 4: Your profile

In this last part of the survey, please rate the following 15 statements on the 7-point scale:

1 - Strongly Disagree
2 - Disagree
3 - Somewhat Disagree
4 - Unsure
5 - Somewhat Agree
6 - Agree
7 - Strongly Agree

1. We should devote some part of our national resources to environmental protection. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

2. It is important to me that we try to protect our environment for our future generations. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

3. The increasing destruction of the environment is a serious problem. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

4. We are not doing enough to protect our environment. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

5. It would mean a lot to me if I could contribute to protecting the environment. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

6. The environment is one of the most important issues that the world is facing. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Statements #7 to #11 are related to sweatshop (a factory or workshop where clothes are made manually).

7. Sweatshop issues should be actively discussed and confronted in society. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

8. Sweatshops violate labor laws. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

9. Sweatshop-based companies damage the interests and rights of sweatshop-free companies. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

10. I am concerned about issues affecting sweatshop workers in apparel manufacturing businesses. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

11. Sweatshops damage the apparel industry. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Statements #12 to #15 are related to eco-labels.

12. Most environmental claims on product labels are true. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

13. Because environmental claims are exaggerated, consumers would be better off if such claims were eliminated, *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

14. Most environmental claims on product labels are intended to mislead rather than inform consumers. *

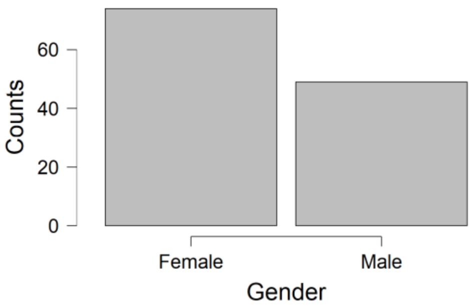
	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

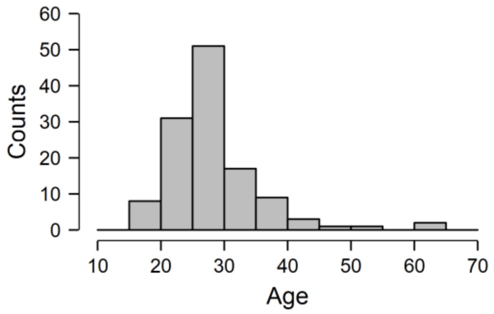
15. I do not believe most environmental claims on product labels. *

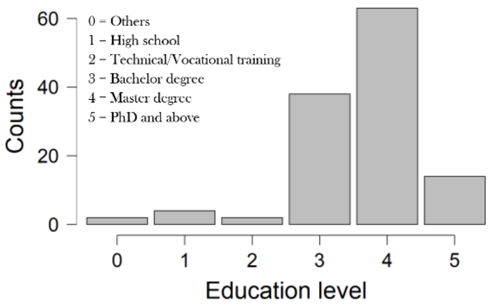
	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

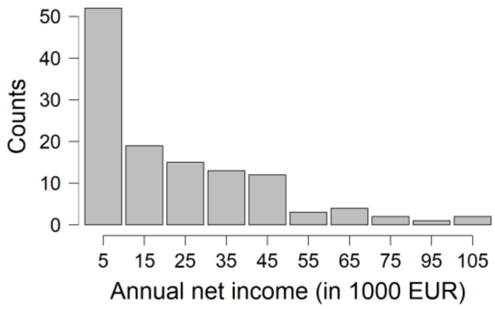
Back Submit

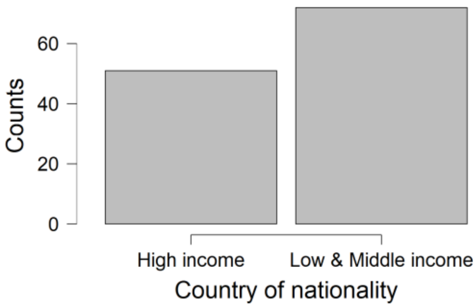
D. DISTRIBUTION PLOTS OF BACKGROUND VARIABLES

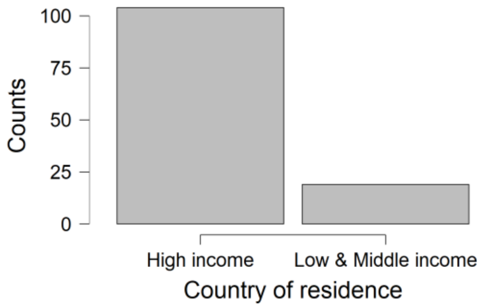


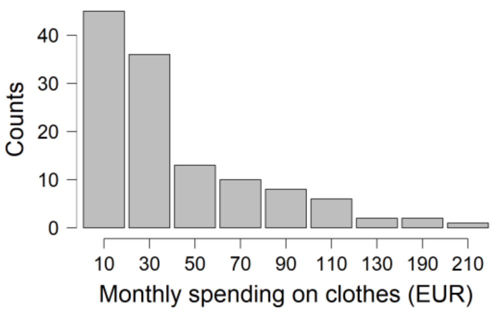


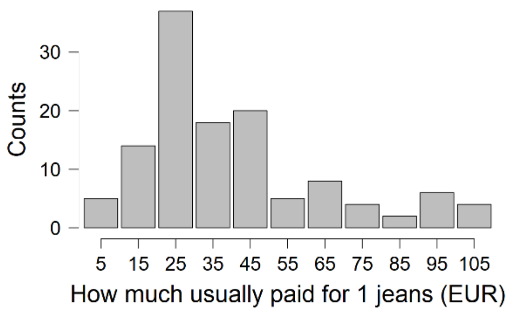


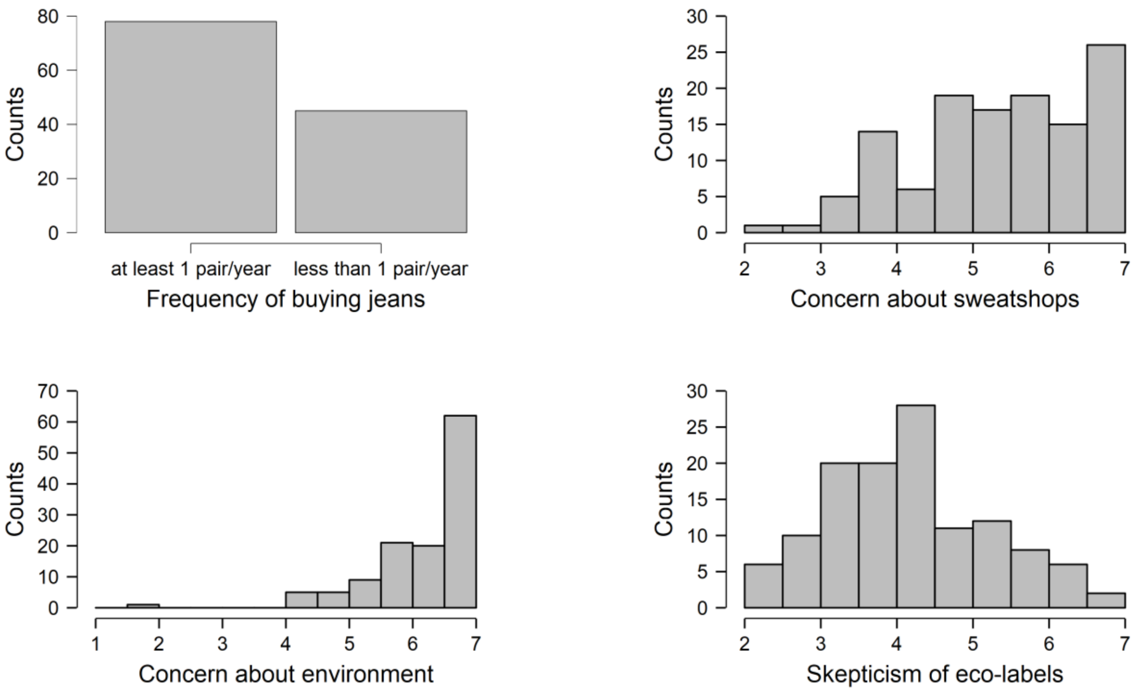











Counts
at least 1 pair/year
less than 1 pair/year
Frequency of buying jeans
Concern about sweatshops
Concern about environment
Skepticism of eco-labels

E. DESCRIPTIVE STATISTICS OF ATTITUDINAL STATEMENTS

	Min	Max	Median	Mean	Standard Deviation
Concern about environment	**1.67**	**7.00**	**6.67**	**6.29**	**0.84**
1. We should devote some part of our national resources to environmental protection.	1.00	7.00	7.00	6.39	0.94
2. It is important to me that we try to protect our environment for our future generations.	3.00	7.00	7.00	6.43	0.91
3. The increasing destruction of the environment is a serious problem.	1.00	7.00	7.00	6.59	0.84
4. We are not doing enough to protect our environment.	2.00	7.00	7.00	6.28	1.07
5. It would mean a lot to me if I could contribute to protecting the environment.	1.00	7.00	6.00	5.95	1.20
6. The environment is one of the most important issues facing the world	1.00	7.00	7.00	6.07	1.33
Concern about sweatshops	**2.40**	**7.00**	**5.40**	**5.41**	**1.15**
7. Sweatshop issues should be actively discussed and confronted in society.	1.00	7.00	6.00	6.02	1.20
8. Sweatshop violates labor laws.	2.00	7.00	6.00	5.57	1.39
9. Sweatshop-based companies damage the interests and rights of sweatshop-free companies.	1.00	7.00	5.00	5.25	1.46
10. I am concerned about issues affecting sweatshop workers in apparel manufacturing business.	2.00	7.00	6.00	5.42	1.47
11. Sweatshop damages the the apparel industry.	1.00	7.00	5.00	4.81	1.51
Skepticism of eco-labels	**2.25**	**7.00**	**4.25**	**4.28**	**1.08**
12. Most environmental claims made on product labels are true*	1.00	7.00	4.00	4.41	1.29
13. Because environmental claims are exaggerated, consumers would be better off if such claims were eliminated	1.00	7.00	4.00	3.81	1.67
14. Most environmental claims on product labels are intended to mislead rather than inform consumers.	2.00	7.00	4.00	4.50	1.39
15. I do not believe most environmental claims on product labels.	1.00	7.00	4.00	4.41	1.53

**Results after reverse coding*

F. MODEL ESTIMATION SYNTAX (IN RSTUDIO)

F1. MNL-5 (Main effects of main variables only)

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list (
  modelName = "MNL-5",
  modelDescr = "MNL-5",
  indivID = "ID", ## ID of participants
  mixing = FALSE ## mixed logit or random distribution parameters)
apollo_control$panelData = FALSE ## define if there are panel data (TRUE if panel data)

#### LOAD DATA
database = read.csv("Data.csv",header=TRUE,sep=";")

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(asc=0, asc_opt_out=0, b_Price=0, b_Origin=0, b_Fiber=0, b_Wash=0, b_Dry=0,
b_Env=0, b_Labor=0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta,
use apollo_beta_fixed = c() if none
apollo_fixed = c("asc_opt_out")

#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate")
{
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
    V[['alt1']]  = asc + b_Price*Price1 + b_Origin*Origin1 + b_Fiber*Fiber1 +
                 b_Wash*Wash1 + b_Dry*Dry1 + b_Env*log(Env1) + b_Labor*log(Labor1)
    V[['alt2']]  = asc + b_Price*Price2 + b_Origin*Origin2 + b_Fiber*Fiber2 +
                 b_Wash*Wash2 + b_Dry*Dry2 + b_Env*log(Env2) + b_Labor*log(Labor2)
```

```
   V[['opt_out']] = asc_opt_out

  ### Define settings for MNL model component
   mnl_settings  = list(
     alternatives  = c(alt1=1, alt2=2, opt_out=3),
     avail           = 1,
     choiceVar    = Choice,
     V               = V
)
  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```

F2. MNL-7 (Adding main effects of background variables)

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list (
  modelName = "MNL-7",
  modelDescr = "MNL-7",
  indivID = "ID", ## ID of participants
  mixing = FALSE ## mixed logit or random distribution parameters)
apollo_control$panelData = FALSE ## define if there are panel data (TRUE if panel data)

#### LOAD DATA
database = read.csv("Data.csv",header=TRUE,sep=";")

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(asc=0, asc_opt_out=0,
              b_Price=0, b_Origin=0, b_Fiber=0, b_Wash=0, b_Dry=0, b_Env=0, b_Labor=0, b_Gender=0,
              b_Residence=0, b_Clothes=0, b_JeansFreq=0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta,
use apollo_beta_fixed = c() if none
apollo_fixed = c("asc_opt_out")

#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate")
{
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
    V[['alt1']]  = asc + b_Price*Price1 + b_Origin*Origin1 + b_Fiber*Fiber1 +
                   b_Wash*Wash1 + b_Dry*Dry1 + b_Env*log(Env1) + b_Labor*log(Labor1) +
                   b_Gender*Gender + b_Residence*Residence + b_Clothes*Clothes +
                   b_JeansFreq*JeansFreq
```

```
  V[['alt2']]  = asc + b_Price*Price2 + b_Origin*Origin2 + b_Fiber*Fiber2 +
                b_Wash*Wash2 + b_Dry*Dry2 + b_Env*log(Env2) + b_Labor*log(Labor2) +
                b_Gender*Gender + b_Residence*Residence + b_Clothes*Clothes +
                b_JeansFreq*JeansFreq

  V[['opt_out']] = asc_opt_out

 ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(alt1=1, alt2=2, opt_out=3),
    avail         = 1,
    choiceVar     = Choice,
    V              = V
)
 ### Compute probabilities using MNL model
 P[['model']] = apollo_mnl(mnl_settings, functionality)

 ### Prepare and return outputs of function
 P = apollo_prepareProb(P, apollo_inputs, functionality)
 return(P)
}
#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```

F3. MNL-8 (Adding interactions)

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list (
  modelName = "MNL-8",
  modelDescr = "MNL-8",
  indivID = "ID", ## ID of participants
  mixing = FALSE ## mixed logit or random distribution parameters)
apollo_control$panelData = FALSE ## define if there are panel data (TRUE if panel data)

#### LOAD DATA
database = read.csv("Data.csv",header=TRUE,sep=";")

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(asc=0, asc_opt_out=0,
        b_Price=0, b_Origin=0, b_Fiber=0, b_Wash=0, b_Dry=0, b_Env=0, b_Labor=0,
        b_Gender=0, b_Residence=0, b_Clothes=0, b_JeansFreq=0,
        b_EnvLabor=0, b_GenderPrice=0, b_EducationEnv=0,
        b_ResidenceEnv=0, b_ResidencePrice=0, b_ConcernSwtLabor=0,
        b_SkepticismLabor=0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta,
use apollo_beta_fixed = c() if none
apollo_fixed = c("asc_opt_out")

#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate")
{
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
```

```
  V[['alt1']]  = asc + b_Price*Price1 + b_Origin*Origin1 + b_Fiber*Fiber1 +
                 b_Wash*Wash1 + b_Dry*Dry1 + b_Env*log(Env1) + b_Labor*log(Labor1) +
                 b_Gender*Gender + b_Residence*Residence + b_Clothes*Clothes +
                 b_JeansFreq*JeansFreq +
                 Price1*(Gender*b_GenderPrice + Residence*b_ResidencePrice) +
                 log(Env1)*(Education*b_EducationEnv + Residence*b_ResidenceEnv) +
                 log(Labor1)*(log(Env1)*b_EnvLabor + ConcernSwt*b_ConcernSwtLabor +
                 Skepticism*b_SkepticismLabor)

  V[['alt2']]  = asc + b_Price*Price2 + b_Origin*Origin2 + b_Fiber*Fiber2 +
                 b_Wash*Wash2 + b_Dry*Dry2 + b_Env*log(Env2) + b_Labor*log(Labor2) +
                 b_Gender*Gender + b_Residence*Residence + b_Clothes*Clothes +
                 b_JeansFreq*JeansFreq +
                 Price2*(Gender*b_GenderPrice + Residence*b_ResidencePrice) +
                 log(Env2)*(Education*b_EducationEnv + Residence*b_ResidenceEnv) +
                 log(Labor2)*(log(Env2)*b_EnvLabor + ConcernSwt*b_ConcernSwtLabor +
                 Skepticism*b_SkepticismLabor)

  V[['opt_out']] = asc_opt_out

 ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(alt1=1, alt2=2, opt_out=3),
    avail         = 1,
    choiceVar     = Choice,
    V             = V
)
 ### Compute probabilities using MNL model
 P[['model']] = apollo_mnl(mnl_settings, functionality)

 ### Prepare and return outputs of function
 P = apollo_prepareProb(P, apollo_inputs, functionality)
 return(P)
}
#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```

F4. Panel ML (Adding heterogeneities and panel effect)

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="Panel ML",
  modelDescr ="Panel ML",
  indivID    ="ID",
  mixing     = TRUE)

#### LOAD DATA
database = read.csv("Data.csv",header=TRUE,sep=";")

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(asc_opt_out=0, b_Purchase=0,
        b_Price=0, b_Origin=0, b_Fiber=0, b_Wash=0, b_Dry=0, b_Env=0, b_Labor=0,
        sigma_Purchase=1, sigma_Env=1, sigma_Labor=1,
        b_JeansFreq=0,
        b_GenderPrice=0, b_ResidencePrice=0, b_ConcernSwtLabor=0, b_SkepticismLabor=0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in
apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c("asc_opt_out")

### Set parameters for generating draws
apollo_draws = list(
  interDrawsType = "halton",
  interNDraws    = 250,
  interUnifDraws = c(),
  interNormDraws = c("draws"),
  intraDrawsType = "halton",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c()
)

### Create random parameters
apollo_randCoeff = function(apollo_beta, apollo_inputs){
  randcoeff = list()
```

```
 randcoeff[["RND_Env"]]          =  b_Env + sigma_Env * draws
 randcoeff[["RND_Labor"]]        =  b_Labor + sigma_Labor * draws
 randcoeff[["RND_Purchase"]]  =  b_Purchase + sigma_Purchase * draws
  return(randcoeff)
}
#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

 ### Attach inputs and detach after function exit
 apollo_attach(apollo_beta, apollo_inputs)
 on.exit(apollo_detach(apollo_beta, apollo_inputs))

 ### Create list of probabilities P
 P = list()

 ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
 V = list()
 V[['alt1']]  = RND_Purchase + b_Price*Price1 + b_Origin*Origin1 + b_Fiber*Fiber1 +
                   b_Wash*Wash1 + b_Dry*Dry1 + RND_Env*log(Env1) + RND_Labor*log(Labor1) +
                   b_JeansFreq*JeansFreq +
                   Price1*(Gender*b_GenderPrice + Residence*b_ResidencePrice)
                   log(Labor1)*(ConcernSwt*b_ConcernSwtLabor + Skepticism*b_SkepticismLabor) +

 V[['alt2']]  = RND_Purchase + b_Price*Price2 + b_Origin*Origin2 + b_Fiber*Fiber2 +
                   b_Wash*Wash2 + b_Dry*Dry2 + RND_Env*log(Env2) + RND_Labor*log(Labor2) +
                   b_JeansFreq*JeansFreq +
                   Price2*(Gender*b_GenderPrice + Residence*b_ResidencePrice) +
                   log(Labor2)*(ConcernSwt*b_ConcernSwtLabor + Skepticism*b_SkepticismLabor)

 V[['opt_out']] = asc_opt_out

 ### Define settings for MNL model component
 mnl_settings  = list(
  alternatives  = c(alt1=1, alt2=2, opt_out=3),
  avail           = 1,
  choiceVar     = Choice,
  V               = V
 )

 ### Compute probabilities using MNL model
 P[['model']] = apollo_mnl(mnl_settings, functionality)
```

```
  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}

#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed,
                 apollo_probabilities, apollo_inputs, estimate_settings=list(hessianRoutine="maxLik"))

#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```