Finding the optimal return policy leniency and adopting rising technologies: A simulation study on Zalando

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ABSTRACT:
This research seeks to reduce e-commerce fashion returns by finding the optimal monetary policy leniency and adoption of Augmented Reality (A.R.) and Customer Profiling Technology (CPT). While A.R. provides virtual try-on, such as clothing filters, on consumers to reduce legitimate returns due to fit issues, CPT tracks personal I.D.s by every return to prevent wardrobing behaviours. A prescriptive model is developed, and a simulation study on Zalando is conducted to investigate these technologies' impact and the conditions that foster the adoption. The results show that (1) a partial refund is more optimal than a full refund, (2) CPT offers significant benefits when e-tailers offer a lenient policy, (3) under high opportunism, A.R. should only be adopted if it is highly effective, and (4) CPT and A.R. together hold significant value under a lenient return policy but offer little value under a restrictive policy. Notably, in some cases, CPT can reverse the impact of A.R. on profits.

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Keywords
e-commerce returns, return policy, customer profiling technology, virtual fitting room, augmented reality, monetary leniency, opportunistic returns, fit uncertainty

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1. INTRODUCTION

E-commerce has been growing tremendously. Euromonitor (2021) estimates that 16% of goods were bought online in 2021, and in 2025, e-commerce will expand by an additional USD 1.4 trillion, accounting for half the growth in the global retail sector. In Europe 2021, most purchases of e-commerce involved clothes, shoes, or accessories, from 68% of e-buyers (Eurostat, 2022).

Due to the absence of "feel and touch" experiences, ordering decisions for fashion products are deemed to carry more risk, making fashion products high-risk purchases (Ha & Stoel, 2004; Levin et al., 2003). Consequently, many fashion e-tailers offer lenient return policies to compensate for a lack of physical experiences, such as generous refunds or return windows (Ofek et al., 2010; Wood, 2001). While E.U. e-tailers are obliged to offer a full refund for returns within 14 days and cannot charge restocking costs, U.S. e-tailers can freely determine their policies if they disclose them online.

This lenient policy results in a high risk of returns (Gelbrich et al., 2017), especially in fashion e-commerce. The leading European fashion e-commerce, Zalando, has an average return rate of 50% globally (Zalando, 2020). A McKinsey Returns Management Survey in 2020 noted a 25% return rate for e-commerce apparel, compared to 20% overall for e-commerce and 10.6% for both offline and online purchases (Ader et al., 2021). These high return rates due to lenient policies may significantly erode profitability and detriment the environment. Meanwhile, a restrictive return policy can reduce return rates but trigger higher perceived risk, resulting in lower purchases and profits. Therefore, it is essential to determine the optimal return policy and the optimal number of returns to maximise profits rather than utilise a strict policy (Gelbrich et al., 2017).

There are two types of returns, namely legitimate and opportunistic. Most returns are legitimate due to misfit or lack of physical experience. Product fit uncertainty is the most popular reason, accounting for 70%-80% of the fashion return (Ader et al., 2021; Rakuten, 2018), which has been proven critical in recent articles (Gallino & Moreno, 2018; Gelbrich et al., 2017; Hong et al., 2014). Meanwhile, the opportunistic returns, or wardrobing, involve buying products deliberately to return them after personal use, like dressing for events or social media. This opportunism causes the most losses to the firm due to the serial returns and borrowing behaviour (Ketzenberg et al., 2020). In the U.S., 33.8% of e-tailers have experienced wardrobing in 2020 (NRF & Appriss Retail, 2020).

Currently, there is a rise in different technologies to tackle these problems. Virtual fitting room (VFR) has become popular to solve fit issues, with Augmented Reality (A.R.) being one of the most popular types. Meanwhile, customer profiling technology (CPT) is the most popular measure to counter opportunism. CPT identifies opportunistic customers by recording each customer's number, frequency, and dollar volume of returns with their I.D. (Akturk et al., 2021). However, when e-tailers use customers' personal information for profiling purposes, customers incorporate a hassle cost of privacy concerns (Casadesus-Masanell & Hervas-Drane, 2015). Consequently, it can hinder purchases and sabotage relationships with legitimate consumers misclassified as opportunistic. In other words, CPT can harm profitability if utilised inaccurately.

Despite the widespread use of these technologies, there is a lack of research on the benefits of using modern technologies in the e-tail returns environment (Ahsan & Rahman, 2022). Additionally, their adoptions are often studied without the impact of return policy leniency. Also, current research lacks an overview of interactions between policy, consumer behaviour, and technology. Ambilkar et al. (2021) suggest a research gap in technology usage and quantitative modelling of returns. Therefore, this research will investigate the impact of these technologies and return policy leniency on profit to fill the gap.

1.1 Objective and Research Question

This research aims to estimate the impact of emerging technologies and determine the optimal return policy's leniency to maximise profits. The research will focus on fashion e-tailers in the U.S., U.K., and E.U., where fashion returns are much more severe than in other regions (Chang & Yang, 2022; Serravalle et al., 2022).

The research question is: *What is the optimal combination of monetary return leniency and adoption of CPT and A.R. to maximise profitability?*

This research question raises two sub-questions as follows:

(1) What is the optimal monetary return policy leniency?
(2) In which conditions is CPT and/or A.R. beneficial to fashion e-tailers?

2. LITERATURE REVIEW

A systematic literature review is conducted to construct a conceptual framework. The review is done via Google Scholar and Scopus with fixed search strings as ("e-commerce" AND "return") and specific strings as ("policy" OR "consumer" OR "technology") to find articles from 2010 to ensure up-to-date research. Also, backward and forward snowballing make the literature review comprehensive (Wohlin, 2014). To ensure the quality of the literature review, this research only uses papers from journals with impact factors higher than 2.00. This research also gathers relevant information from market research reports, online newspapers, and blogs from fashion e-tailers and technology providers to explore recent insights and trends.

2.1 Return Policy

Previous research classifies return policies on a scale of lenient and restrictive. Janakiraman & Syrdal (2015) conducted a meta-analytic literature review and conceptualised leniency into five factors: (1) Time leniency on the return window; (2) Monetary leniency on monetary restrictions like refund amount or a non-refundable shipping fee; (3) Effort leniency on the consumer's required efforts to return products; (4) Scope leniency on the scope of returnable items; and (5) Exchange leniency on the feasibility of cash refunds. In other words, lenient policies have traits like long return window, full refund in cash, and effortless return procedures with various categories. Meanwhile, restrictive ones have a short return window, store credit refund or partial refund, and complex return procedures with limited scope. As leniency and restrictiveness are in a scale rather than discrete groups, this research will refer to "lenient policies" as the policies closer to the lenient side rather than pure lenient ones.

Currently, many fashion e-tailers offer lenient return policies to compensate for the risk of lacking physical examination of online purchases (Ofek et al., 2010; Wood, 2001). However, a lenient policy induces many problems. It increases return probability by fuelling excessive or unnecessary buying (Hjort & Lantz, 2016; Kang & Johnson, 2009; Lantz & Hjort, 2013). Consequently, it significantly hampers profits (Gelbrich et al., 2017; Gustafsson et al., 2021; Hjort & Lantz, 2016) and produces tremendous waste (Dutta et al., 2020; Pålsson et al., 2017). Additionally, the lenient policy is more vulnerable to opportunistic return behaviours (Bahn & Boyd, 2014; Lantz & Hjort, 2013; Ülkü & Gürler, 2018), which further amplifies the negative impact.

Nevertheless, fashion e-tailers should not halt offering lenient policies as it has shown many benefits. A lenient policy can signal high quality both pre- and post-purchase (Bonifield et al., 2010; Wood, 2001), introduce higher consumer loyalty and long-term relationship (Griffis et al., 2012; Ramanathan, 2011; Rokonuzzaman et al., 2021), and prompt consumer trust (Oghazi et al., 2018; Pei et al., 2014). Therefore, it reduces risk perception and increases purchases (Bower & Maxham, 2012; Hjort & Lantz, 2016; Lantz & Hjort, 2013; Pei et al., 2014; Wood, 2001). Some studies suggest that a lenient policy is not necessarily evil and can help e-tailers outsmart rivals (Rokonuzzaman et al., 2021), be a marketing, profit-enhancing strategy (J. Chen & Grewal, 2013) and even a competitive weapon (Mukhopadhyay & Setaputra, 2007). Therefore, the goal is to optimise policy leniency to minimise the returns without eroding the profits.

This research will focus on monetary leniency - the most crucial factor for consumers when evaluating policy leniency. Additionally, monetary leniency can impact purchases and returns, conspicuously affecting profitability (Abdulla et al., 2021). From this point, when referring to leniency, this research means monetary-specific leniency.

2.1.1 Monetary Leniency on Returns and Profits

Monetary leniency represents a refund amount against the purchase value (Su, 2009), a non-refundable restocking fee (Shulman et al., 2011), or both (Janakiraman & Syrdal, 2015). Some papers view it as a refund rate rather than an amount (Alptekinoglu & Grasas, 2014; Chu et al., 1998; Mukhopadhyay & Setaputra, 2007). Many papers refer to high monetary leniency, full refund, as Money-back Guarantee (MBG) (B. Chen & Chen, 2017; McWilliams, 2012; Walsh & Möhring, 2017).

Return shipping fee can be a non-refundable portion because consumers can bear this cost. However, e-tailers that offer both a full refund and a free return will provide a refund amount higher than the price paid for a product (Abdulla et al., 2019). Therefore, the refund amount regarding product price and the return fee will be addressed separately in this research to account for all possible costs that e-tailers must bear. Consequently, this research will follow Janakiraman & Syrdal (2015) 's definition that monetary leniency is determined by the refund amount paid for the product and the return fee. This definition allows for robustness in adjusting the leniency level to optimise profitability rather than a binary decision like MBG. Accordingly, a more lenient policy allows for a full refund or a higher refund with a free return, while a stricter policy will impose a lower refund portion or a higher refund fee and require consumers to pay the return shipping fee.

Although some empirical studies show that monetary leniency is less effective in curbing returns than in stimulating purchases (Abdulla et al., 2021; Wood, 2001) or even does not affect returns at all (Janakiraman & Syrdal, 2015), some studies still prove that high leniency can strikingly worsen return rates (Walsh & Möhring, 2017). Papers that model consumer heterogenous valuations illustrate that monetary leniency affects decisions to purchase and return the product. Specifically, a consumer relies on the expected utility to make a purchase/return decision, a function of product valuation and refund amount; hence, higher leniency also instigates higher returns (Akçay et al., 2012; Shulman et al., 2009; Su, 2009).

Although lenient policies can foster multiple business benefits, there is a consensus that a full-refund (excessively lenient) policy may be overly generous and often suboptimal under a wide range of conditions (Abdulla et al., 2019; Bonifield et al., 2010). However, the optimal monetary leniency still varies according to different operational conditions. With homogeneous consumers, the optimal refund amount equals the salvage value (Akçay et al., 2012; Shang et al., 2017; Su, 2009). Altug & Aydinliyim (2016) find a full-refund policy profitable only when the salvage value minimally deviates from the original price. Meanwhile, B. Chen & Chen (2017) recommend a looser condition for a full refund with only a positive net salvage value. McWilliams (2012) finds that the full refund only benefits low-price e-tailers.

The results might differ, but most papers suggest that a partial refund is more optimal than a full refund. However, most e-tailers still offer full refund policies (Akçay et al., 2012): 51% of North American and European e-commerce sites already offer free returns, and 8% will offer such a policy in 2021 (Chevalier, 2022). High monetary leniency also has many benefits, such as signalling high quality, lowering risk perception, and significantly stimulating purchases. Therefore, the goal is neither to minimise nor to maximise leniency but to find the optimal point to maximise profitability (Gelbrich et al., 2017).

Articles that also examine policy leniency and its impact on returns often ignore restocking costs or incorporate them into product cost or salvage value (Akturk et al., 2021; Fan et al., 2022; Su, 2009; Ülkü et al., 2013). Meanwhile, the articles that examine return cost impact often exclude refund amounts (Shulman et al., 2009, 2011). By not determining a separate variable for the return cost and only examining the refund rate of a maximum of 100% of the product price, or only accounting for the return shipping fee, these articles often disregard other costs like examining, storing, cleaning, and reselling the returns (Rakuten, 2018; Schiffer, 2019). Consequently, this simplification will be misleading, especially when the return costs are notably high or low. As a result, the impact of the monetary leniency lever is not evaluated thoroughly. Therefore, this research will treat the restocking cost separately from the return shipping fee.

2.1.2 Regional Regulations

In the state members of E.U., consumers have the right to return the online purchase within 14 days after receiving it for any reason and are entitled to a full refund without any restocking fee, including the delivery cost but excluding the return cost. However, there are still additional requirements to this right, such as conditions for returned items like being unsealed or unused (European Parliament, 2011). For simplification, this research assumes that all returned items meet the requirements for full refunds. Hence, a model that includes a full refund, no restocking fee, and an imposable return shipping fee is developed for E.U. e-tailers.

In the U.S., there are no federal laws regarding returns and refunds. Out of 50 states, 11 states declare that unless the e-tailers appropriately disclose their refund policies, consumers are entitled to a full refund within 10-30 days after the purchase. The other 39 states impose no laws regarding return and refund, so the return and refund depend on each e-tailer's policy (FindLaw, 2019). In other words, as long as e-tailers explicitly declare their return policy, they can charge the consumers a restocking fee or determine the refund amount they want. Therefore, this research assumes that all e-tailers appropriately disclose their return policies and develops a model with adjustable refund amounts so that U.S. e-tailers can find the optimal refund amount.

2.2 Consumer Return Behaviour

Pei & Paswan (2018) define two types of returns behaviour: legitimate and opportunistic. Legitimate returns stem from acceptable reasons, including product defects or buyers' remorse of fit issues. However, defects depend on e-tailer's manufacturing, which is out of this research scope. Additionally, they only account for 5% of the number of returns (Fan et al., 2022), so they can be excluded. Sometimes, customers mistakenly consider the product faulty while it is not because they cannot physically investigate the product. Without a physical try-on, it is difficult to determine the product fit (size, style), which results in a high return rate in fashion e-commerce (Hong et al., 2014).

Opportunistic returns are immoral or unethical return behaviours encompassing merchandise borrowing, tag switching, and fraudulent returns (Pei & Paswan, 2018), which may be fuelled frivolously by lenient policies (Bahn & Boyd, 2014; Hjort & Lantz, 2012; Ülkü & Gürler, 2018). These behaviours were first termed “deshopping” for the premeditated and arguably inappropriate return for reasons other than product defects (Schmidt et al., 1999). Similarly, “retail borrowing” targets customers who deliberately return a product after using it (Hjort & Lantz, 2012; Piron & Young, 2001). These behaviours are also known as “wardrobing” (Shang et al., 2017), “fraudulent returning” (Harris, 2008), or “abusive returns” (Ketzenberg et al., 2020). This research will use these terms interchangeably and follow the definition of Hjort & Lantz (2012) to focus on unethically borrowing the products. The fraudulent returns, such as price switching and shoplifting, are excluded in this research because they are straightforward criminal activities, out of the research scope, and disparate from opportunistic behaviours (Akturk et al., 2021; Griffis et al., 2012).

However, product returns are not necessarily evil. Petersen & Kumar (2009) suggested that moderately allowing returns could maximise firm profits. Ketzenberg et al. (2020) found that while abusive returners are highly unprofitable, high returners are four times more profitable than non-returners and low legitimate returners are twice as profitable as high legitimate returners. Therefore, the goal is to minimise unprofitable returns.

For simplified modelling, this research will classify opportunism based on transactions rather than consumers, following “the deshopping” definition from Schmidt et al. (1999). In other words, one consumer can conduct legitimate returns if the products do not match and opportunistic returns if the products match. In fact, opportunistic returners might also have some items they purchase without deliberate intention to return. Therefore, by identifying opportunism based on transactions rather than consumers, this research can create a model to minimise opportunistic returns while not hindering profitable legitimate ones and achieve a more accurate classification.

2.3 Reducing Legitimate Returns – Augmented-Reality Virtual Fitting Room

Current technologies that reduce fit uncertainty include size/style recommendations, fit visualisation, and fit recommendations. Size and style recommendations are based on consumers’ preference; fit visualisation simulates clothes on a body; and fit recommendation suggests suitable sizes with consumers’ personal inputs like heights, weights, or ages. While size/style and fit recommendations are widely applied, fit visualisation is not popular (Miell et al., 2018). Fit issues still account for 70% of the returns, signifying that recommendation technologies are insufficient, and fit visualisation can tackle them. For example, virtual fitting room (VFR) technologies can support try-on and fit assessment (Gustafsson et al., 2021; Miell et al., 2018).

Lee & Xu (2020) classify VFR into seven types based on accuracy, attractiveness, and interactivity to consumers. While 3D body scanner has the highest accuracy, it is bulky to implement as consumers must scan themselves physically at the stores (Gustafsson et al., 2021; Lee & Xu, 2020). Additionally, many women respond negatively to whole-body scanning (Grogan et al., 2015), making 3D body scanners unfriendly to e-tailers and consumers. Similarly, a robot mannequin provides high body accuracy but requires the physical existence of robots. Meanwhile, 3D avatar, 3D customer model, and V.R. fitting room have the lowest accuracy (Lee & Xu, 2020), so their applications might reduce uncertainty perception but not necessarily solve the fit issues. Therefore, this research will proceed with Augmented Reality (A.R.), which is highly accurate and interactive but does not require cumbersome physical installations (Lee et al., 2021; Lee & Xu, 2020), making it easily transferrable to vendors (Erra et al., 2018).

A.R. scans and tracks body movements, allowing consumers to try on various augmented clothes via a camera-based technology. Therefore, they enhance consumers’ visualisation experiences, offering a realistic fitting experience as if in an actual fitting room (Lee & Xu, 2020). Many fashion e-tailers have developed AR-based virtual try-on in their mobile phone apps, such as clothing filters, to reduce returns, including Adidas, Crocs, New Balance, Zara, Converse (Caboni & Hagberg, 2019; Vyking, n.d.), and recently Amazon (Amazon, n.d.).

A.R. can increase engagement, purchase intention, referrals (Beck & Crié, 2018; Brengman et al., 2019; Javornik, 2016; Park & Yoo, 2020), improve customer loyalty and retention (Beck & Crié, 2018; Bonnin, 2020), and reduce product risk perceptions (Bonnin, 2020). Compared to physical try-on, A.R. can accurately convey the sizes and colours, helping consumers choose suitable items. Additionally, A.R. can predict style, garment details, and coordination with other items (Baytar et al., 2020). Especially, A.R. assists consumers in understanding how products fit them personally by providing information in different degrees, reducing fit uncertainty (Caboni & Hagberg, 2019). Although the result of A.R.’s impact on fashion returns is still lacking, many similar VFR applications on fashion returns or A.R. applications in other industries have shown positive results. More than 90% of Americans currently use or would consider using A.R. for shopping, and 98% of those who have used A.R. found it helpful (Ipsos & Google, 2020).

Like any other type of technology, AR/VFR also face risks of online security and data breaches. Recording, storing, and analysing faces has fostered privacy concerns. For example, in 2019, privacy and data breaches were reported as consumers’ top legal concern and companies’ top second challenges (Perkins Coie, 2019). In practice, the beauty e-tailer Ulta was sued for collecting users’ biometric and geometric facial data from A.R. without consent, risking identity theft (Biron, 2021). From smart glasses to smartphones, A.R. devices are vulnerable to privacy threats (S. Chen et al., 2018). However, research suggests privacy concerns might not reduce A.R. use (Poushneh, 2018; Rauschnabel et al., 2018; Smink et al., 2019). The intrusiveness of branded A.R. face filter apps, or A.R. beauty try-on, is also reported not to have adverse effects on consumer responses (Smink et al., 2019); Nevertheless, A.R. try-on is not mass applied, and consumer responses might still change in the future.

Currently, the simulation of materials still has low accuracy (Erra et al., 2018; Kim & LaBat, 2013; Song & Ashdown, 2015). A.R. generally has not been accurate enough for perfect fit evaluation of tightness (Baytar et al., 2020), and localisation and tracking accuracy must be improved for an entirely realistic experience (Bastug et al., 2017). Nevertheless, many corporations like Walmart, Snap, and start-ups are investing in fashion A.R. and working on hyper-realistic cloth, and A.R. clothes are expected to look realistic soon (McDowell, 2021).

2.4 Reducing Opportunistic Returns - Customer Profiling Technology

CPT has been referred to as “shopping tracking technology” (Kang & Johnson, 2009) and CPT (Akturk et al., 2021). To identify opportunism from recorded transactions, CPT requires personal I.D.s during the return process and uses statistical models to decide whether to accept the return (Akturk et al., 2021; Kang & Johnson, 2009; The Retail Equation, 2022). For example, The Retail Equation (TRE), the leader in CPT, examines the e-tailer's offline and online transactions linked with government-issued I.D.s to analyse the consumer's transaction history with the e-tailer to identify possible abusive behaviours. Many major e-tailers have used CPT, such as Home Depot, Sephora, JCPenny, Victoria's Secret, Best Buy, CVS Pharmacy, Dick's Sporting Goods, and Nike (CNBC, 2013; Peterson, 2018; Safdar, 2018), but not all e-tailers use it. Consequently, this research will investigate the conditions, specifically monetary leniency and consumer behaviours, which influence the adoption of CPT based on profitability enhancement.

Although CPT can prevent abusive returns, it can also generate hassle costs that detriment profitability. One of the main costs of adopting CPT is the privacy concern arising when the e-tailers retrieve consumers' personal information for CPT (Akturk et al., 2021; Casadesus-Masanell & Hervas-Drane, 2015). For example, TRE declares to retrieve consumers' government-issued I.D. number, name, address, and date of birth (The Retail Equation, n.d.), which is considered intrusive despite TRE's commitment not to share the information with other parties or clients (Safdar, 2018). CPT has led to a privacy lawsuit against Best Buy in Florida in 2011 (CNBC, 2013) and numerous complaints against the brand on social media (Safdar, 2018), tarnishing the brand image and sabotaging future purchases.

Two types of errors can occur with a predictive model like CPT. Type I errors occur when legitimate returners are misclassified as opportunistic, impelling negative attitudes toward the e-tailer (Dailey & Ülkü, 2018). Type II errors occur when opportunistic returns are incorrectly classified as legitimate, which is less severe but can unintentionally promote return abuse with lacking penalties. Besides predictive accuracy, the model's effectiveness shall account for the cost and frequency of misclassification (Ketzenberg et al., 2020). Therefore, type I error will be accounted for as a decrease in customer demand, while type II error will represent the opportunistic returns that pass the system.

3. RESEARCH DESIGN

This research will construct a quantitative model to answer the research question. Quantitative modelling is based on a set of variables over a specific domain, among which quantitative and causal relationships are defined. Quantitative modelling can explain partly real-life behaviour and capture decision-making problems (Bertrand & Fransoo, 2002). Therefore, it is a suitable choice, given that the conceptual framework is constructed as a tangled network of interacting variables that reflects the real-life purchase/return decision-making process.

Additionally, this research will conduct a simulation study to investigate problems. According to Law (2014), simulation can investigate real-world problems where the complexity and stochastic properties of the system render it unfeasible for evaluation with traditional analytic methods. Furthermore, simulation allows one to estimate an existing system's performance under some projected operating conditions to answer what-if questions. The simulation will be done on Zalando, Europe's largest online-only fashion retailer, for abundant public data (Reuters, 2021). Additionally, Zalando also possesses a substantially high return rate, with a 50% return rate globally and a 60% return rate in Germany (Zalando, 2020).

Law (2003) formulated a seven-step approach to conduct a simulation study, which will be the outline of this research. Firstly, the problem is formulated, partly done in Chapters 1 and 2, and repeated in Section 4.1. Secondly, the conceptual model will be constructed based on the literature and real-world scenarios in Sections 4.2 and 4.3. Then, relevant data will be collected in Section 5.1. Thirdly, the conceptual model is validated on its logic and assumptions aligned with the literature in Section 5.2. Next, this research will combine the fourth, fifth, and sixth steps to program the model and design experiments in Section 5.3. Finally, the results are presented and discussed in Chapter 6.

To make the simulation more accurate, it is preferable to get datasets from fashion e-commerce operating in countries facing much more severe returns like in U.S., U.K., and E.U. (Chang & Yang, 2022; Serravalle et al., 2022; Yu & Kim, 2019). Additionally, the datasets should include information regarding variables mentioned in the conceptual framework. If the datasets are unavailable, relevant statistics will be gathered from research papers, official reports, and government statistics. The statistics should be recent, preferably within five years.

4. SIMULATION CONSTRUCTION

This chapter will encompass the first two steps of a simulation study. The problems and context are formulated in Section 4.1, and the model adopted is critically assessed and modified in Section 4.2.

4.1 Formulating Problems and Context

While the returns introduce more costs, moderately allowing them can stimulate profit (Petersen & Kumar, 2009). Consequently, this simulation study aims to find the optimal policy leniency and decisions to adopt the rising technologies (A.R., CPT) that maximise profitability. Specifically, aligned with the research question, the simulation study serves two purposes: (1) to find the optimal monetary leniency and (2) to find conditions in which CPT and A.R. benefit e-tailers.

As discussed, E.U. e-tailers, including Zalando, must offer a full refund and cannot charge a restocking fee, making their return policy always lenient. Meanwhile, as U.S. e-tailers can freely determine their leniency, their policies can be either restrictive or lenient. Therefore, the model must be robust enough to help all e-tailers determine the optimal policy leniency and decisions to adopt the rising technologies.

4.2 Model Assumptions and Modifications

This research will modify Akturk et al.'s (2021) model and exclude the section on fraudsters. Additionally, this research will adjust considerably different settings to investigate the research question. The modifications are as follows.

1. While Akturk et al. (2021) use the model to identify the optimal price and return, this research only seeks the optimal policy leniency and tests the sensitivity based on Zalando's current situation.
2. Akturk et al. (2021) assume that the salvage value is lower than the product cost, which is not applicable in many cases. Currently, with a short product return cycle, many fashion e-tailers like Zalando and Asos quickly resell the 97% of returned products in the primary market, maintaining high salvage value (ASOS, 2021; Zalando, 2020). Therefore, this research will remove the restriction on the salvage value to make the model more robust.
3. Akturk et al. (2021) exclude the decision variable of return shipping fee and restocking cost, which also significantly affect the purchase/return decisions and the e-tailer's profitability. This research will explicitly include the restocking cost and return shipping fee to evaluate their impact on profitability.
4. For the lack of literature and evidence about the goodwill cost of CPT, this research removes this variable to ensure the model validity. Additionally, this research demonstrates the monetary gains from correctly hindering optimistic returns through

decreasing returns, and reducing return costs, thereby simplifying the model.

5. Akturk et al. (2021) do not set a limit to opportunistic returns, so there will be cases where none of the sold items is kept, which is unrealistic. This research will limit the size of opportunistic returns, so they cannot replace all net sales.

4.3 Conceptualising the Model

4.3.1 The Return Process

There are two designs of the supply chain to handle returns. The first way is a linear design, such as Amazon resells returned items to third parties and outsources return management issues. Alternatively, e-tailers can manage these issues themselves with closed-loop design and reintroduce returns into the primary or secondary market after refurbishment, remanufacturing, or recycling (Difrancesco et al., 2018). In practice, some key players like Zalando and Asos manage to resell many returned items into the primary market. Therefore, this research follows a closed-loop supply chain design and assumes that all returned products will be resold at their salvage value.

For simplification, opportunistic returns are defined as returns of matching products, while legitimate returns are defined as returns of mismatched products. Based on the literature review, a consumer's decision-making process is summarised in Figure 1.

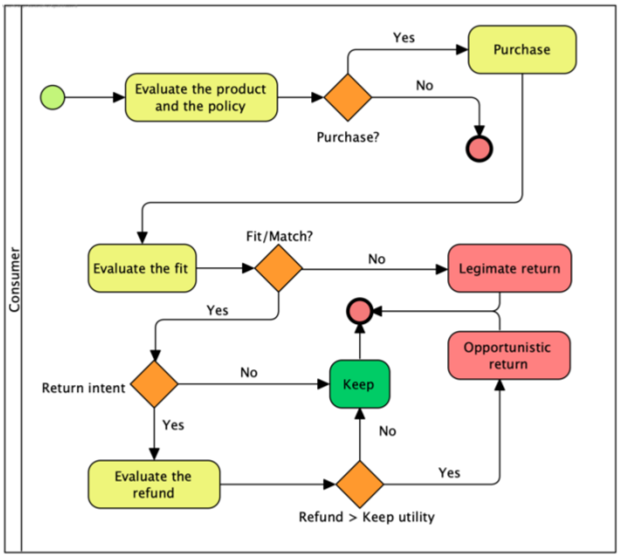

Figure 1. A consumer's decision-making process

While some e-tailers set a minimum order value for free returns, for simplification, this research will assume that e-tailers apply the same return shipping fee for every return despite its value. As stated, the goal variable is profit. Based on the return process, variables contributing to profits are sales price, salvage value, purchasing cost, refund amount, and return cost. Besides, consumer decisions of purchasing or returning the products also influence the profits. Therefore, other decision variables are accounted for in the model, summarised in Table 1 and explained in the latter sections.

4.3.2 Basic Model (RAM) and Policy Leniency

Consumers are segmented by their intrinsic valuation, denoted by v, of a product unit (Akturk et al., 2021; Xu et al., 2018). The valuation illustrates how much the consumers like a product. In other words, the higher the valuation, the higher the chance that the consumers will purchase or keep an item. Following previous literature, this research will assume that the consumer relies on the expected utility to make a purchase/return decision, a function of product valuation and refund amount (Akçay et al., 2012; Shulman et al., 2009; Su, 2009).

Table 1. Summary of Variables and Notation

Symbol	Variable (per product unit)
v	**Consumer valuation.** A normalised variable representing consumer valuation of the item.
c	**Product cost.** The normalised cost to make an item, including both materials and labour.
p	**Sales price.** The normalised price that the consumer pays if buying the item.
$r_{\%}$	**Refund rate.** The ratio between the refund amount over the sales price.
d	**Return shipping fee.** The normalised shipping fee for returning the item.
r	**Refund amount.** The normalised refund amount consumers receive if they return the item, including the shipping fee. $r = r_{\%}p + d$. Hence, r also represents the overall monetary leniency.
t	**Consumer consumption rate.** A normalised variable representing the value an opportunistic consumer will gain from wardrobing the item.
R	**Proportion of returned items.** The proportion of returns among the total market.
S	**Proportion of net sales.** The proportion of sold and non-returned items among the total market.
λ	**Mismatch probability.** The probability that the item does not match the consumer.
s	**Salvage value.** The normalised value that the e-tailer can gain from reselling the returned item.
γ	**Maximum proportion of opportunistic returns.** The maximum proportion of opportunistic returns in sales of matching items.

As defined, opportunistic consumers will consume the products unethically during the return window. With opportunism presence, the optimal refund is a function of opportunistic size and consumption rate (Shang et al., 2017). Therefore, a variable of consumption rate per product unit is created to represent the value that an opportunistic consumer will gain from wardrobing the products. Therefore, the higher the consumption rate, the more the opportunistic consumer can gain, and hence, the more opportunistic returns. With a consumption rate *t* and a valuation v of the product, a consumer is assumed to gain a total *tv* utility from using the product before returning it.

Firstly, the threshold valuation $\hat{v}$ of whether to make a purchase, is that of the opportunistic consumer indifferent between making a purchase. In other words, consumers will purchase if their valuation exceeds this threshold $\hat{v}$. If the product fits with a probability of $1 - \lambda$, the boundary opportunistic consumer will gain utility from using it ($t\hat{v}$) and lose utility from the non-refunded amount ($-p + r$). If the product does not fit with a probability of λ, this consumer will lose utility from the non-refunded amount. The expected utility for this boundary consumer is $E(\hat{v}) = (1 - \lambda)(t\hat{v} - p + r) + \lambda(-p + r)$

Secondly, the threshold valuation $\bar{v}$ of whether to return the product is the valuation of the boundary consumer indifferent whether to return the product. Specifically, consumers with a valuation greater than $\bar{v}$ will keep the matching product. This research assumes that the consumers will always return a mismatched product as it generates no value and utility.

However, when the product is a match, the consumers can still decide whether to return the product. Therefore, a consumer returning a matching product discloses opportunistic behaviour (Schmidt et al., 1999). If the refund amount exceeds the value obtained from keeping the product or $r > (1-t)\bar{v}$, opportunistic consumers will return the items to maximise their utility (Akturk et al., 2021).

Thirdly, some consumers make a legitimate purchase without the deliberate intention of return. With $\dot{v}$ denoting the boundary consumers' valuation, any consumer with a valuation exceeding this threshold will make a purchase and only return mismatched items. Therefore, if the item matches, they will gain a net utility from their consumption and price paid, and if the item mismatches, they lose a net utility from the non-refunded amount. The expected utility function is $E(\dot{v}) = (1-\lambda)(\dot{v} - p) + \lambda(-p+r)$.

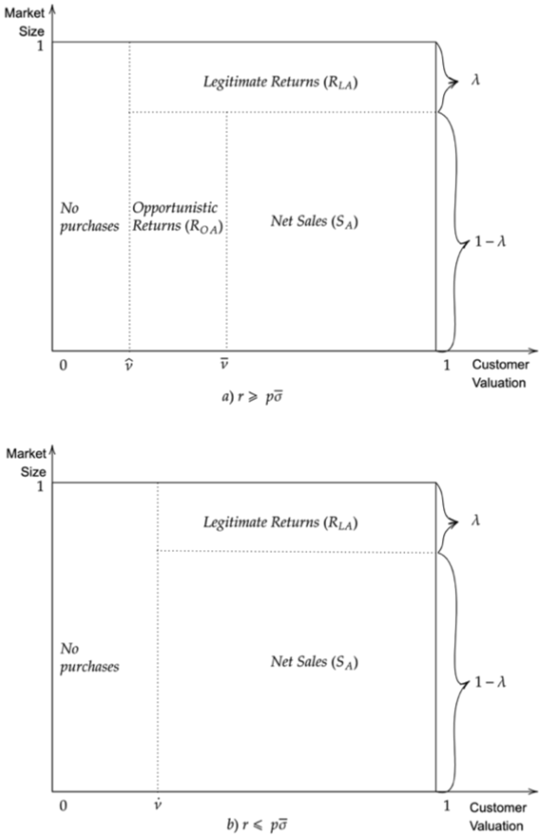

Figure 2. The Proportion of Net Sales and Returns

Because only consumers with a valuation higher than $\hat{v}$ will buy the product, and only those with a higher valuation than $\bar{v}$ will keep the matching product, the opportunistic returns only happen when $\hat{v} < \bar{v}$, or $r \geq p\frac{1-t}{1-\lambda t}$. With $r = p\sigma$, when $\sigma > \bar{\sigma} = \frac{1-t}{1-\lambda t}$, or $\hat{v} < \dot{v} < \bar{v}$, the opportunistic segment is always positive. In contrast, when $r < \sigma$, or $\hat{v} > \dot{v} > \bar{v}$, the opportunistic segment will disappear (Akturk et al., 2021). These implications are visualised in Figure 2.

In Figures 2a and 2b, the market size is separated into mismatching λ and matching $(1-\lambda)$. In Figure 2a, any valuation exceeding $\hat{v}$ will result in a purchase. The purchase in mismatching group λ will be returned as legitimate ones. For the matching group, as valuation exceeding $\bar{v}$ will keep the items, this region is considered non-returned purchases, so-called net sales. Meanwhile, as the valuation lies between $\hat{v}$ and $\bar{v}$ belonging to the matching group will return the matching items, this region is identified as opportunistic returns. In Figure 2b, the opportunistic group disappears, and consumers only purchase if their valuation exceeds $\dot{v}$.

Based on the previous implications and Figure 2, the following equations are formulated:

1. The legitimate returns are the purchase of non-matching items:
$$R_L = (1 - \min\{\hat{v}, \dot{v}\})^{+}\lambda$$
2. The opportunistic returns are the returns of matching items, limited by a maximum of γ fraction of matching sales:
$$R_o = \max\left(R'_o;\ \gamma(R'_o + S')\right)$$
3. The net sales are the non-returned purchase of matching items:
$$S = \min(S'; S' + R'_o - R_o).$$

with $R'_O = (\bar{v} - \hat{v})^{+}(1-\lambda)$; $S' = (1 - \max\{\bar{v}, \dot{v}\})^{+}(1-\lambda)$.

For every product sale, the profit is (p –c), which is the price less the product cost. The refund amount is determined by the refund rate times the product sales price and the decision of whether to charge restocking cost and return shipping fee, or $r = r_{\%}p + d$. For simplicity, the restocking cost is incorporated into the return rate. Hence, if $r_{\%}$ is 100%, the e-tailer will offer a full refund of product value but still charge the restocking cost; and when $r_{\%}$ exceeds 100%, the e-tailer will cover the restocking cost.

For every product returned, the profit is obtained from the price and salvaged value less the product cost and return cost, denoted by (p – c + s – r). Therefore, the returns can still be profitable depending on salvage value, refund amount, and return cost. The profit function is determined as below:

$$\text{Profit(r)} = S(p-c) + (R_L + R_O)(p - r + s - c)$$
$$st{:}\, r \geq p\sigma$$

Based on Figure 2, it is evident that the profit functions vary based on the relative values between $\hat{v}$, $\dot{v}$ and $\bar{v}$. Specifically, in case (a) with $\hat{v} < \dot{v} < \bar{v}$, or $r \geq p\bar{\sigma}$, the profit objective becomes as follows:

$$\text{Profit}_\text{A}(r) = S_A(p-c) + (R_{LA} + R_{OA})(p - r + s - c)$$
$$st{:}\, r \geq p\max\{\sigma, \bar{\sigma}\}; r \leq (1-t)$$

In case (b) with $\hat{v} > \dot{v} > \bar{v}$, or $r \leq p\bar{\sigma}$, the opportunistic segment will disappear, and the profit function becomes as follows:

$$\text{Profit}_\text{B}(r) = S_B(p-c) + (R_{LB})(p - r + s - c)$$
$$st{:}\, r \geq p\sigma; r \leq p\bar{\sigma}; p - \lambda r \leq 1 - \lambda$$

4.3.3 Impact of Technology

As discussed, A.R. can increase engagement and reduce perceived risks to stimulate purchases. Let h_{AR} ($1 \leq h_{AR}$) denote the demand inflation, so when h_{AR} is 1, A.R. does not stimulate new purchases. Additionally, as A.R. can reduce mismatch probability, let θ ($0 \leq \theta \leq 1$) denote the adjusting factor of mismatch probability due to A.R. When θ is zero, A.R. does not reduce fit issues at all, and when θ is one, A.R. can alleviate all fit uncertainty. The new mismatch probability is $\lambda' = \lambda(1-\theta)$.

If legitimate returns are misclassified as opportunistic, consumers can grow negative attitudes toward the e-tailer (Dailey & Ülkü, 2018), eroding future purchases and customer lifetime value. Additionally, CPT comes with a hassle cost as it requires personal I.D.s at the point of return (Akturk et al., 2021), so it is not always profitable. Therefore, to determine in which conditions e-tailers should adopt the technology, this research will adopt the model of Akturk et al. (2021). As TRE declare to examine transaction patterns to give recommendations per transaction (The Retail Equation, n.d.), this research assumes that CPT can classify opportunism by transactions.

Let (1-α) and β respectively denote type I and type II errors. (1-α) demonstrates the probability of legitimate returns being misclassified as opportunistic, so α denotes the fraction of the legitimate returns that are correctly classified. Similarly, β indicates the probability that opportunistic returns can pass the system, so (1-β) of opportunism will be correctly classified. This research assumes that (1-α) of consumers who make legitimate returns falsely rejected by CPT will stop making purchases, so only α of consumers will keep making purchases.

As mentioned, CPT comes with various hassle costs, which will deflate the demand. Therefore, a demand deflation is incorporated into the model, denoted by h_{CPT} ($0 \leq h_{CPT} \leq 1$). Consequently, the model without CPT has a hassle cost of zero, or $h_{CPT} = 0$. Because CPT is only beneficial when opportunism is present as in Figure 2a, the following equations are formulated with the constraint on the size of opportunism.

1. The legitimate returns are limited to α fraction of consumers correctly identified:
$$R_L = (1 - \bar{v})^{+} \lambda' \alpha h_{CPT} h_{AR}$$
2. The opportunistic returns are limited to β fraction not identified by CPT and γ fraction of the total matching sales:
$$R_o = \max\,(R_o'; \ \gamma(R_o' + S'))\beta h_{CPT} h_{AR}$$
3. The net sales are limited to α fraction of consumers who keep making purchases:
$$S = \min\,(S'; R_o' + S' - R_o)\alpha h_{CPT} h_{AR}$$

with $R'_O = (\bar{v} - \hat{v})^{+}(1 - \lambda')$ and $S' = (1 - \bar{v})(1 - \lambda')$.

Especially, because CPT is only beneficial when opportunism is present, the CPT adoption is only applied to the case in Figure 2a. The profit function becomes as follows:

$$\text{Profit}_{\text{A}}(r) = S_A(p - c) + (R_{LA} + R_{OA})(p - r + s - c)$$
$$st{:}\, r \geq p \max\{\sigma, \bar{\sigma}\};\ r \leq 1 - t.$$

5. SIMULATION STUDY

This chapter will discuss the following steps of a simulation study: data collection, model validation, and experiment design.

5.1 Data Collection

On the market level, among the 30% rate of return, 70% of which is due to fit issues. Consequently, 21% of all sales are returned due to mismatch (Ader et al., 2021). As Zalando's return rate is 60% in Germany (Zalando, 2020), one-third of which is due to fit issues, implying that 20% of all items are returned due to mismatch (Henkel, 2019). As Zalando's mismatch probability approximates the market's, the market's statistic is taken for generic implications.

The price of 6000 women's clothing items (out of 297,017 items) was randomly scrapped on Zalando's website on May 14th. As the distribution is heavily right-skewed, only product prices over €100 are removed, resulting in 5739 items left. Then, the prices are normalised between 0 and 1, so the price of €100 is 1. The process is in Appendix A. The product unit cost is estimated based on Zalando's annual reports on Orbis and product price (Bureau van Dijk, n.d.). From 2012 to 2021, Zalando's gross margin follows a normal distribution with a mean of 45.53% and a standard deviation of 1.34%. Therefore, the product unit cost, calculated based on the gross margin, is about 54.5% of the product price.

Zalando will charge a €2.95 shipping fee for any order under €20 (Zalando, n.d.), implying that the return fee is also about €2.95 per order or 0.03 after normalisation. However, some e-tailers even charge up to €10, 0.1 after normalisation, like Lichi and Nelly (Lichi, n.d.; Nelly.com, n.d.). A study showed that about 25% of U.S. e-tailers charge more than $10 (parcelLab, 2021). Therefore, the return shipping fee is assumed to vary between 0 (e-tailers shift the cost to consumers) and 0.1 (e-tailers bear the high cost). The restocking fee should not cost more than 20% of the product price (Alptekinoglu et al., 2009). Consequently, the restocking cost of the return, such as storage, inspection, and redistribution, is assumed to be less than 20% of the product price. While Zalando and E.U. e-tailers cannot charge restocking costs (r%=120%), other values of 80% and 100% are tested for more generic implications to other U.S. e-tailers. The lower bound is 80%, as many mainstream e-tailers pledge to offer an 80%+ refund policy (Akturk et al., 2021).

The salvage value of a returned product is estimated via the current Zalando report. Zalando announces that up to 97% of returned items have the perfect condition and can be sold again through the primary market (Zalando, 2019), so their salvage value can be up to 100%. With 3% that cannot be sold, this research will assume that their salvage value is 0% to compensate for the previous optimistic assumption. Therefore, the average salvage value is 97%. However, this research will assume the average salvage value to vary between 30% and 90% to account for the worse scenarios: e-tailers cannot resell these products as they pledge or must sell the returned products at a discount.

As discussed, A.R. can improve the fit issue to some extent and have few negative consequences due to A.R.'s hassle cost. For example, A.R. facilitated Macy's to reduce its return rate to less than 2%, while the average rate in the furniture industry is 5%-7% (Boland, 2019). Zeekit, a VFR provider for Macy's and Adidas, claim to reduce return rate by 36% (Business Insider, 2020). However, it should also be noted that clothes are much more difficult to visualise than shoes and furniture. As the impact of A.R. on mismatch probability is still unclear, the simulation will take values from 0 to 0.9, or from A.R. having no impact on mismatch probability to A.R. can reduce 90% mismatch probability. While A.R. was reported to stimulate purchases up to 200% (Biron, 2021; Galer, 2021), this research only assumes that A.R. can stimulate purchases by 20% to avoid over-optimism.

Additionally, there is no available information on the proportion of opportunistic returns, so it is assumed not to exceed 80% of the total sales of matching items. As mentioned, if one-third of all returns are due to fit issues, the other two-thirds relate to other reasons. Even if they are all opportunistic, they will contribute 40% of all returns or 50% of all sales of matching items. This research extends the limit to 80% to account for the worst scenario that e-tailers must face.

5.2 Model Validation

The base model is adapted from Akturk et al. (2021), which was peer-reviewed and published in Omega, a journal with an impact factor of 7, and cited seven times within one year. Therefore, the base model has been approved by experts.

This research modifies the base model, which still allows it to reflect some literature implications as follows. Firstly, the model implies that the lenient policy encourages more purchases (Bower & Maxham, 2012; Hjort & Lantz, 2016; Lantz & Hjort, 2013; Pei et al., 2014; Wood, 2001). The higher refund amount r will lower the purchase threshold, $\dot{v}$ and $\hat{v}$, stimulating more purchases with $E(\hat{v}) = 0$, $\hat{v} = \frac{p-r}{(1-\lambda)t}$, or $E(\dot{v}) = 0$, $\dot{v} = \frac{p-\lambda r}{1-\lambda}$.

Secondly, the model indicates that the lenient policy will reduce the chance that the consumers keep the product as they see more value in returning, aligning with literature that a more lenient policy will result in higher returns (Akçay et al., 2012; Shulman et al., 2009; Su, 2009). The higher refund amount r will increase the keeping threshold $\bar{v}$, thereby reducing the net sales number with $U(\bar{v}) = 0, \bar{v} = \frac{r}{1-t}$. Additionally, in Figure 2a, the model implies that opportunistic returns increase when the policy becomes more lenient or the refund amount r approaches the price p with $r \geq p\frac{1-t}{1-\lambda t}$,.

The model simplifies some real-life situations but can easily be adjusted with the variables. Firstly, consumers may not return their items although they do not fit, then the mismatch probability can be adjusted to convert these mismatch items into net sales. Secondly, the return shipping fee should be calculated by every order rather than an item. However, the return shipping fee can be adjusted to reflect the fee per item based on the average order value. Similarly, many e-tailers set a minimum order value for free returns, which can be reflected by adjusting the shipping fee to align the proportion of free and charge returns and order value. Additionally, Appendix B also proves that the consumption rate is proportional to opportunism in the market.

5.3 Experiment Design

The model and simulations are conducted in Python for its interpretability, versatility, and efficiency. Every experiment will get the product price from 5739 normalised data points, and the margin is randomly generated from a normal distribution with a mean of 45.53% and a standard deviation of 1.34%. Hence, the product cost can be calculated from the product price and the margin, as $c = p(1 - margin)$. Therefore, every experiment has 5739 trials, which can ensure a high validity.

Table 2. Summary of Simulation Settings

Symbol	Name	Parameters
s%	Salvage value (% of price)	[0.3, 0.6, 0.9]
λ	Mismatch probability	0.21
t	Consumption rate	Uniform [0;1]
d	Return shipping fee	[0; 0.1]
r%	Refund rate	[0.8; 1; 1.2]
γ	Maximum proportion of opportunistic returns in sales of matching items.	0.8
θ	Reduction (%) in mismatch probability due to A.R.	[0; 0.5; 0.9]
h_{AR}	Demand adjusting factor due to AR	1.2
α	Fraction of the legitimate returns correctly classified	0.95
β	Fraction of the opportunistic returns passing the CPT	0.4
h_{CPT}	Demand adjusting factor due to CPT	0.95

The experiments take setting parameters as in Table 2. The return fraction is simulated between 0.8 to 1.2, implying scenarios that the e-tailers refund 80% to 100% of the price and up to 120% if they do not charge the restocking costs. Although Zalando only operates in E.U. markets and must abide by full monetary leniency, the scenarios of partial refund are still conducted for inferences for e-tailers in the U.S. The return shipping fee is varied between 0, if the e-tailers shift the cost to the consumers, to 0.1, if the e-tailers bear all the return fee.

CPT is assumed to have decent accuracy and a moderate hassle cost, with α = 0.95, β = 0.4 and h_{CPT} = 0.95, which means that 60% of opportunism is eliminated while only 5% of legitimate customers are mislabelled. The adoption of CPT will result in hassle cost of privacy, reducing the demand by 5%.

This research will conduct four experiments to answer the research question. Firstly, an experiment is conducted in Section 6.1 to find the optimal monetary leniency in the absence of the rising technologies. Hence, e-tailers can still adjust their return policy to improve profitability if the technologies cannot help. The second and third experiments will find the conditions of return leniency and attained salvage value that make CPT and A.R. beneficial, respectively, in Sections 6.2 and 6.3. Finally, an experiment is simulated in Section 6.4 to evaluate the interaction between monetary leniency, CPT, and A.R.

6. SIMULATION RESULTS

In the results of the following simulations, E.U. retailers can take implications from experiments with r% = 1.2 as they cannot charge restocking costs and must offer full refunds. Meanwhile, U.S retailers can take any implications from any experiment.

6.1 The Optimal Monetary Leniency

A simulation of monetary leniency is conducted to find the optimal policy leniency. Output in Figure 3 implies the following findings. Firstly, the higher the monetary leniency, including high refund rate, no restocking cost, and free return, the lower the profit. Secondly, opportunistic returns can become profitable in some cases. For example, when the refund rate is sufficiently low (80%), the salvage value is high (90%), and consumers must bear the return shipping fee (d=0), the e-tailers still make a profit from every returned item. Hence, the high number of opportunistic returns are profitable to e-tailers. Thirdly, U.S. e-tailers can consider adopting a restrictive monetary policy if they face remarkably high opportunism or attain low salvage value to hinder unprofitable returns. Most of the time, shifting return shipping fee to consumers is more profitable for e-tailers. However, under low opportunism, a partial-refund policy (r%=0.8) will be more profitable if e-tailers bear the return shipping fee to compensate for the non-refundable amount.

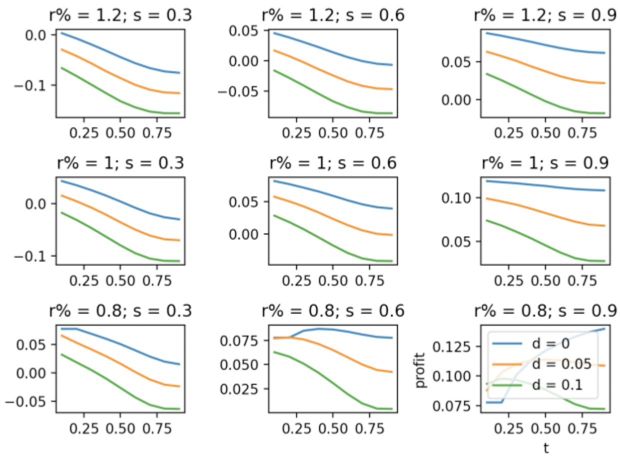

Figure 3. Simulation of Policy Leniency on Profit

This result infers that a full refund is not as optimal as a partial refund. Under any salvage value, the most optimal policy is never to offer a full refund with no restocking fee. Additionally, this result infers that a full refund (r% = 1.2) is only profitable if the salvage value minimally deviates from the selling price (s% = 0.9). Zalando and other E.U. e-tailers, obliged to a full refund without charging a restocking fee, can still make profits despite high opportunistic returns by striving for high salvage value (90% of the price) and/or shifting (partly) return shipping fees to consumers. This high salvage value is possible as Zalando and Asos claim that 97% of returned items are resold in the primary market, signifying the expected salvage value of about 90% (ASOS, 2021; Zalando, 2020).

6.2 When is CPT beneficial?

A simulation with CPT adoption is compared with the basic return abuse model (RAM) to find conditions that favour CPT adoption, with output in Figures 4 and 5. These figures deduce that CPT is remarkably beneficial in a highly lenient monetary policy and low salvage value. In other words, e-tailers should adopt CPT when returns are tremendously unprofitable. However, CPT becomes less effective when the policy becomes more restrictive or when the salvage value increases. Indeed, in these cases, e-tailers can make profits over returns, which will be eliminated by 60% due to CPT. Additionally, a restrictive policy is already a gatekeeper for opportunism, so it will reduce the effectiveness of CPT.

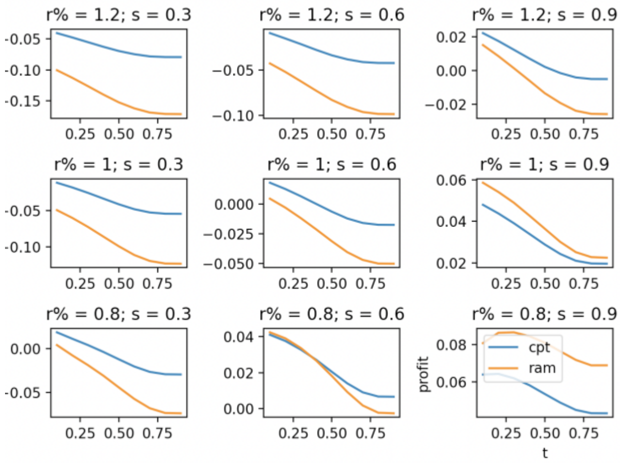

Figure 4. CPT adoption impact on profit when e-tailers must bear a high return shipping fee (d=0.1)

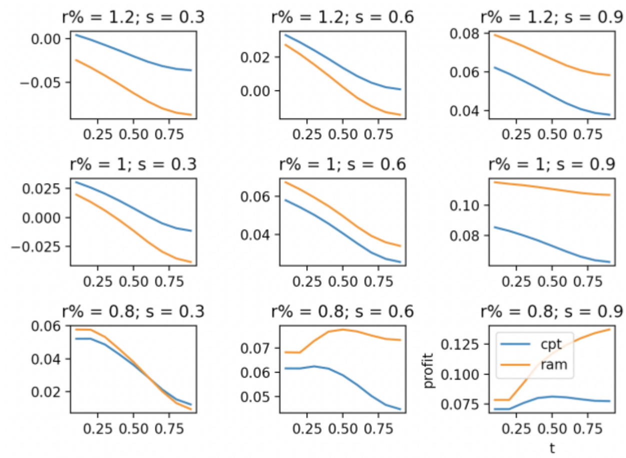

Figure 5. CPT adoption impact on profit when consumers must bear all return shipping fees (d=0)

If E.U. e-tailers must bear high return shipping fees or poor salvage value, they should adopt CPT to reduce the negative effect. However, they should not adopt CPT if they make profits over returns by shifting return shipping fees to consumers and/or bearing relatively low shipping fees and maintaining a high salvage value. In this case, Zalando attains a very high salvage value (s%=0.9), so they should adopt CPT if they must bear a high return shipping fee. Alternatively, they do not need CPT if they shift return shipping fees to consumers.

A sensitivity test is done with the demand reduced by 50% to 90% due to the hassle cost. The simulation output is in Appendix C, which also yields the same implications: CPT is only beneficial when e-tailers make a considerable loss on every return, in the presence of (1) highly lenient monetary policy, free but outrageous return fee, and/or (2) poor salvage value.

6.3 When is A.R. valuable?

Unlike CPT, A.R. have not been reported to impose any hassle costs on consumers yet. Therefore, a simulation of A.R.'s effectiveness is conducted, with a reduction (%) of mismatch probability ranging from 0% to 90%, to investigate the conditions in which A.R.'s high effectiveness is valuable.

The simulation output is in Figure 6 and Appendix D. The result shows that A.R.'s impact on profitability is more prominent in low opportunism. Indeed, when opportunism is low, most returns are legitimate, so A.R.'s impact is more prominent. However, the high opportunism cost will outweigh the reduction in legitimate return cost, making A.R.'s impact more trivial. Therefore, under high opportunism, all e-tailers in U.S. and E.U. should only adopt A.R. if their effectiveness is outstandingly high.

Interestingly, under a restrictive policy (r%=0.8, d=0), the profit curves change by the salvage value. When salvage value is low (or high), e-tailers cannot (or can) make profits over returns, so the profits will erode (or increase) when opportunism increases. However, when the salvage value is moderate (60% of the price), the interactions between legitimate returns, opportunistic returns, and sales become complicated, and profit changes in a parabola-like curve with opportunism. Therefore, an additional experiment is conducted to investigate the interaction between policy leniency and A.R. adoption.

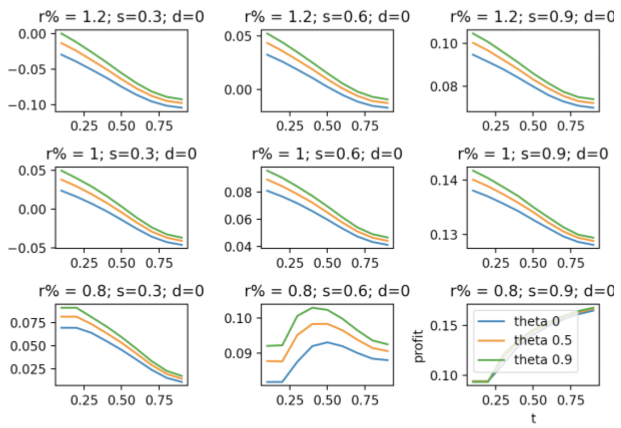

Figure 6. A.R. adoption impact on profit when consumers must bear all return shipping fees (d=0)

6.4 Interaction of Policy and Technologies

The previous simulations show that while CPT is beneficial under a lenient policy with a low salvage value, A.R. is beneficial under high opportunism if it can outstandingly reduce mismatch probability. Therefore, a simulation is conducted to investigate the favourable conditions for adopting these two technologies. The simulation output is in Figure 7 and Appendix E.

The simulation infers that these technologies are highly beneficial under a lenient policy. However, it is preferable not to use the technology when e-tailers can still make profits over returns. Figure 7 infers that when salvage value is high enough, e-tailers can still make a profit over every return. In the case of a high refund amount, the proportion of opportunistic returns overshadows the net sales. Therefore, the reduction of return cost due to A.R. is not significant enough to compensate for eliminating profits from 60% opportunistic returns due to CPT, making the adoptions undesirable. In Appendix E, the simulation of a more lenient monetary policy shows a similar result: when profit over a returned item is high (high salvage value and moderate refund amount), it is desirable not to use these technologies.

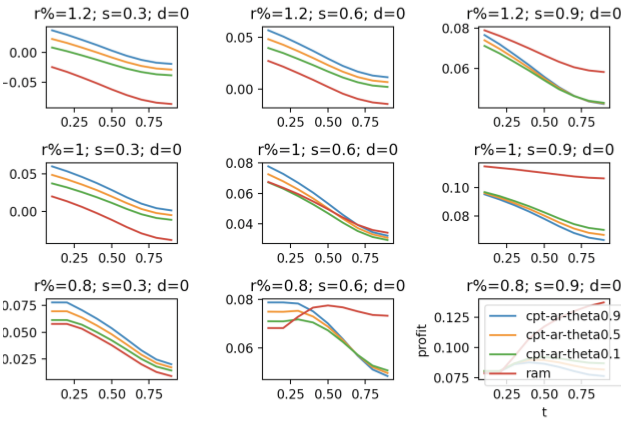

Figure 7. Simulation of A.R. & CPT on Profitability (d=0)

In some cases, CPT reverses A.R.'s effect on profit, or the higher-accuracy A.R., the less profitable. A.R. replaces many legitimate returns with opportunistic returns and net sales when profitable returns. However, as CPT removes 60% of opportunistic returns, a substantial source of profit, the more effective A.R. becomes less profitable.

The implication for Zalando, E.U. e-tailers, and U.S. e-tailers with lenient policies is that they should not adopt these two technologies if they can still make profits over returns, either by maintaining high salvage value or by shifting return fees to consumers. However, if the e-tailers want to provide free returns or cannot attain high salvage value, these technologies are highly beneficial as they can eliminate unprofitable returns. Adopting these technologies is also beneficial for U.S. e-tailers facing unprofitable returns for any reason.

7. DISCUSSIONS

This research adjusts an existing quantitative model to incorporate the impact of monetary return policy, AR-based VFR, and CPT to find the optimal combination of these factors. The research applies the model to Zalando simulation study to help Zalando and similar fashion e-tailers determine the optimal monetary leniency and decide whether to adopt A.R. and CPT.

Firstly, if the technologies are not adopted, partial refunds are more profitable to e-tailers than full refunds, which aligns with the literature (Abdulla et al., 2019; Bonifield et al., 2010; Shang et al., 2017). Additionally, they might consider shifting return fees to consumers when the opportunistic size is large. Despite concerns that charging a return shipping fee will hinder purchases, recently, Zara started charging a minimal fee of £1.95 in the U.K. for online returns via posts, paving the way for other e-tailers to follow and reshaping consumer expectations to pay for the return shipping fee (Ryan & RetailWire, 2022). Additionally, if retailers want a pure lenient policy for market drivers, including a full refund, no return fee, and no restocking cost, they should strive to maximise the reselling prices of the returned items, which supports the study of Altug & Aydinliyim (2016).

Secondly, CPT holds remarkable benefits when (1) the policy is highly lenient (mainly applicable to E.U. e-tailers) and/or (2) the salvage value is significantly low. In these cases, e-tailers make huge losses per return, so CPT will improve profits by hindering opportunism. Meanwhile, U.S. e-tailers have more freedom to charge restocking costs or offer partial refunds to generate profits over opportunistic returns. However, CPT eliminates this profit source and might even erode more profits due to its hassle cost of privacy. Therefore, CPT holds little value under a restrictive monetary return policy. This finding supports the study of Akturk et al. (2021).

Thirdly, e-tailers should adopt A.R. only if its effectiveness is notably high under high opportunism. A.R.'s effectiveness, the extent to which A.R. can reduce mismatch probability, is more prominent when opportunism is low. Indeed, when opportunism is high, the opportunistic return cost overshadows the legitimate return cost, making A.R.'s impact less prominent. Therefore, under high opportunism, if A.R.'s effectiveness is not mediocre, the minimal profit improvement might not be worth the hassle of adopting A.R. Additional evaluation, including investment cost, is needed for further decisions.

Finally, Zalando and e-tailers who offer highly lenient policies should not adopt both A.R. and CPT if they can shift the return shipping fee to consumers and the salvage value minimally deviates from the selling price. On the other hand, if U.S. e-tailers can profit over every return by either restrictive policy or high reselling prices, adopting both technologies might harm profits.

Notably, the fourth simulation also shows that in some cases, when opportunistic returns are profitable, CPT can reverse the effect of A.R. on profitability. As A.R. reduces mismatch probability, it converts legitimate returns into net sales and opportunistic returns. Meanwhile, CPT hinders opportunism, so the more effective A.R. will result in fewer profits due to CPT. Therefore, e-tailers must be careful when adopting these technologies together. However, this result stems from the assumption that a mismatch return by an opportunistic consumer is still counted as a legitimate return. Therefore, further research, especially empirical studies, is needed to validate this finding.

8. RELEVANCE & LIMITATIONS

8.1 Theoretical Relevance

Firstly, this research builds a quantitative model of monetary leniency and two rising technologies, A.R. and CPT, on fashion e-commerce returns and profits. The model is robust to regulations of the U.S. and E.U. on refund policies. It extends the prior work and integrates a usually neglected component in monetary leniency literature - restocking cost and shipping fee. If the e-tailer does not charge restocking costs, the profitability will be influenced by a refund amount that can exceed the order value. Additionally, a variable of return shipping fee is separated from the return amount to increase flexibility in determining monetary leniency and accuracy in evaluating its effect on profitability. This research also fills the lack of research in applying rising technologies to reduce e-commerce returns. The result confirms findings in previous literature on optimal monetary leniency that a partial refund is more optimal than a full refund (Abdulla et al., 2019; Altug & Aydinliyim, 2016; Bonifield et al., 2010; Shang et al., 2017) and conditions in which CPT is beneficial (Akturk et al., 2021).

8.2 Practical Relevance

The research provides a robust model for both U.S. and E.U. e-tailers to analyse the effectiveness of CPT and AR-based VFR technologies against both legitimate and opportunistic returns. The model is robust enough that both U.S. and E.U. e-tailers can use it and adjust it to reflect their business. Additionally, this research applies the model to the case of Zalando, the leading European fashion e-tailer with a strikingly high return rate, to illustrate a clear example of model application. E-tailers can learn from this research that (1) a partial refund is more optimal than a full refund; but if a full refund is obligatory, then e-tailers should strive for a high reselling price; (2) CPT holds substantial value only under high opportunism; (3) under high opportunism, A.R. should be adopted only if they can remarkably reduce mismatch probability; and (4) in some cases, CPT can reverse the effect of A.R on profits.

8.3 Limitations and Future Research

This research has the following limitations. Firstly, the research estimates parameters based on available reports, research, and public data from various sources. Therefore, the parameters in use might not be the most accurate and are vulnerable to bias. Additionally, as the price and cost are taken from Zalando, the result is not generalisable to all e-tailers. Secondly, the research simplifies the consumer decision-making process. Fraudulent returns are excluded. The policy leniency is also only investigated upon the monetary aspect, assuming that consumer valuation purely depends on monetary value, while the other four leniency levers also matter. Other essential determinants like cultures, demographics, or price level also impact purchase and return decisions. Thirdly, this research simplifies the effects of technology adoption. For example, this research ignores fixed and variable costs that can fundamentally affect the adopting decisions, such as installing, developing, or licensing these technologies. Especially with a new and growing technology like A.R., the investment cost can be enormous. Additionally, how CPT algorithms work is ambiguous, which determines its accuracy and whether it hinders opportunism by consumers or by transactions, weakening the model's underlying assumptions. Fourthly, all variables in this paper are normalised within 0 and 1, which does not yield exact solutions, but only gives some sense of general implications. Additionally, the simulation is done on an item level instead of an order level. Meanwhile, return decisions are also based on the fee relative to the order value. Finally, the dynamics between returner types and return types are complex. A consumer can make both legitimate and opportunistic returns, entangling the categorisation.

These limitations infer some recommendations for future research. Firstly, future research can investigate the impact of the other four levers of policy leniency on returns and their interactions with rising technologies. Especially, exchange leniency is the second most crucial lever to consumers but still lacks research (Abdulla et al., 2021). Additionally, some levers like time leniency (return window) and scope leniency will considerably impact salvage value, contributing to the final profits (Difrancesco et al., 2018). Secondly, future research can also examine the impact of fraudulent returns on optimal policy leniency, rising technologies to counter them, and the interaction between different return types and technologies. A.R. also needs more research about the effectiveness, hassle, cost of privacy, and their impact on profits. CPT's underlying algorithm also needs examination. Thirdly, empirical research is needed to validate these findings, especially on the interaction between A.R. and CPT. The dynamics between returner types and return types also need further clarification and smart categorisation.

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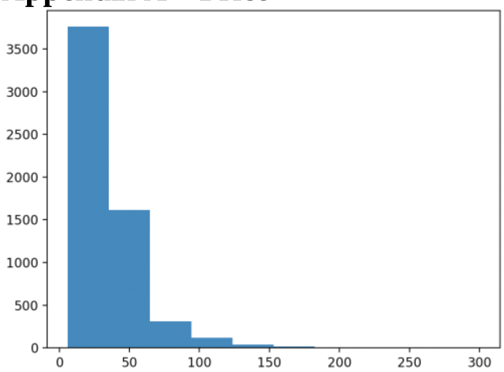
APPENDIX

Appendix A – Price



	Clean selling price
count	5872
mean	35.3176
std	23.6396
min	5.99
25%	19.99
50%	29.99
75%	39.99
max	299.95

Figure 8. Histogram and Descriptive Statistics of Scraped Prices

The histogram shows that the price is significantly right-skewed: while the 75th percentile price is 39.99, the maximum price is 300. Therefore, only prices lower than 100 are kept and normalised between 0 and 1 in Python. The result is in Figure 8. About 2% of the data points were removed.

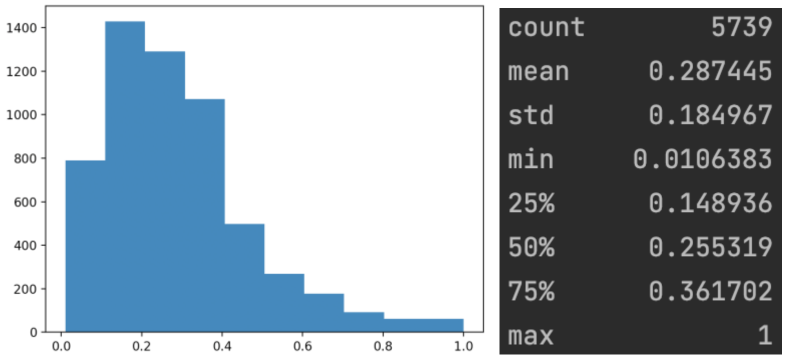


Figure 9. Histogram and Descriptive Statistics of Cleaned and Normalised Prices

Appendix B - Consumption rate and Opportunistic Returns

Firstly, a simulation of consumption rate, monetary leniency, and product price is conducted to visualise their effects on legitimate and opportunistic returns and sales. The simulation output infers that no matter the price and monetary leniency, as the consumption rate increases, the opportunistic returns also increase while the sales decrease, but the legitimate returns barely change. The legitimate returns barely change, which is reasonable as these legitimate consumers buy the products without deliberate intention to return them, so their returns should only be affected by mismatch probability. Therefore, they shall not be (much) affected by the consumption rate. Meanwhile, to optimise their utility, the opportunistic returners will determine whether the residual value after consumption exceeds the refund amount when deciding whether to return. Therefore, opportunistic returns increase along with consumption rates, which are much higher with high refund amounts and prices. Consequently, the net sales decrease.

This simulation implies that the consumption rate reflects the contribution of opportunistic returns. Therefore, the following simulations will be done on consumption rate for simplification, but the implication will be made on the contribution of opportunistic returns.

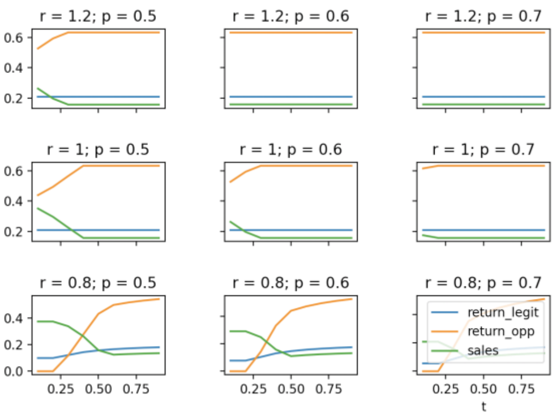


Figure 10. Simulation on Consumption Rate effect

Appendix C – Sensitivity on h_{cpt}

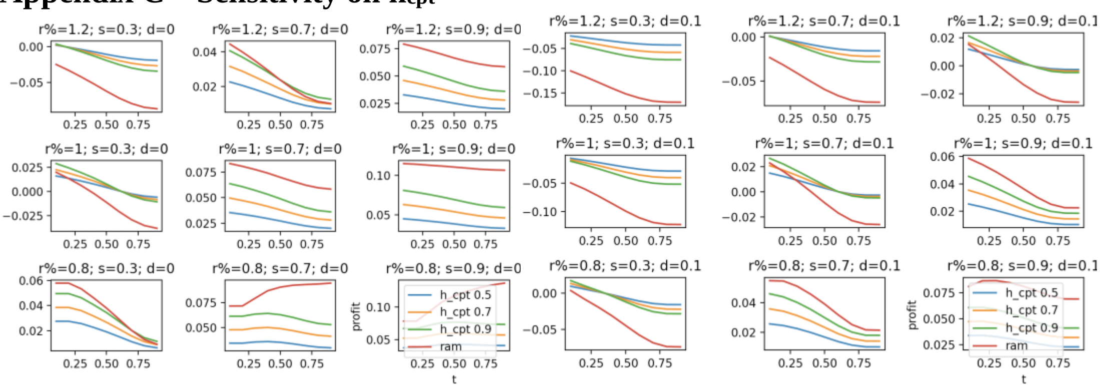


Figure 11. Sensitivity test on hcpt

Appendix D - A.R. simulation

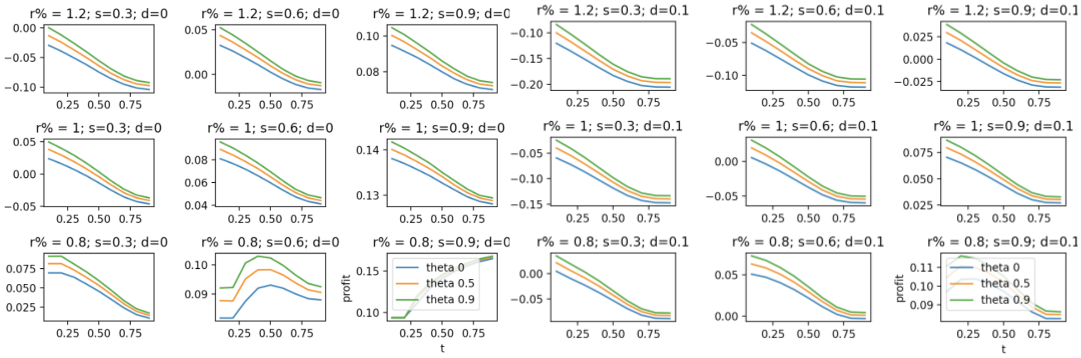


Figure 12. Simulation of A.R. impact on Profits

Appendix E - CPT and AR

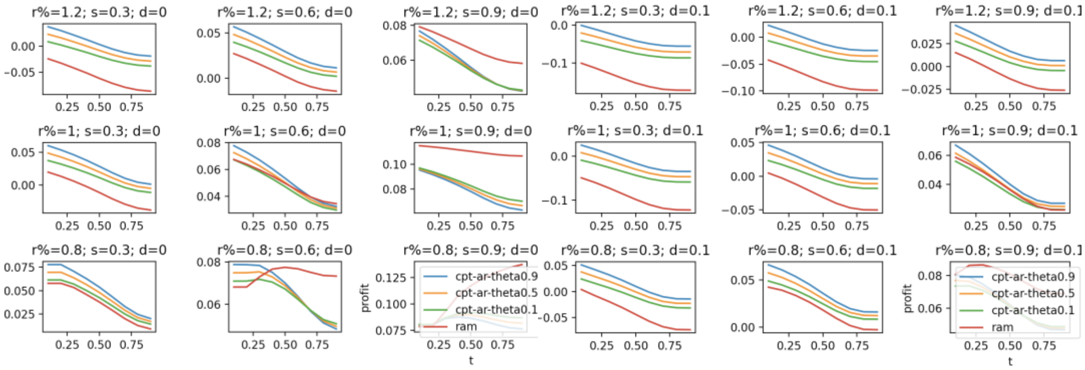


Figure 13. Interaction between policy and technologies